Including Ramping Constraints in the Electric Capacity Expansion Model

by

Sarah Sleiman

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Management Sciences

Waterloo, Ontario, Canada, 2015

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final versions, as accepted by my examiners.

I understand that my thesis may be electronically available to the public.

Abstract

In the long term electricity capacity expansion problem, operators attempt to make decisions years ahead of time on what generator types to invest in in order to meet future electricity needs. In such a model an approximate electricity demand forecast is used. Furthermore, short term generation variables such as ramping capabilities are ignored and reserved for short term planning models. Such simplified long term models have historically yielded good results due to the straightforward nature of operational details that are mainly related to fairly predictable demand patterns. With the increasing penetration of less predictable renewable energy sources however, operators of a system are expected to need to respond to added variability on the supply side of the system. Generators within a system will also need to have the ability to meet such variability and will potentially require higher ramping capabilities in order to respond to the intermittency of renewable energy sources.

The work in this thesis illustrates that capturing short term constraints, such as the ramping constraints originally found in unit commitment models, in the long term capacity expansion model may result in a more realistic power output and capacity mix when planning future generation investments. Furthermore, a new set of constraints are also added to the model in an attempt to maintain some chronology that is required when dealing with the short term ramping constraints.

Data from the Ontario Long Term Energy Plan (LTEP) and the Integrated Power System Plan (IPSP) is used for testing. In comparison with the original capacity expansion model, it is found that the inclusion of the ramping constraints yields a different investment plan that is concluded to be more realistic.

Acknowledgements

First and foremost, many thanks go out to my supervisor, Professor David Fuller, for his expertise, guidance, patience and encouragement. This work would not have been possible without him.

In addition, I would like to extend my gratitude to my readers, Professor Samir Elhedhli and Professor Stanko Dimitrov, for their feedback and suggestions.

I would also like to thank Helen Jiang for her continuous friendship. The past two years wouldn’t have been as enjoyable without her.

Last, but definitely not least, my utmost appreciation and gratitude goes out to my family. I am the person I am today because of their unconditional love and support.

Table of Contents

List of Figures

List of Tables

1 Introduction

Energy in general and electricity in particular, are crucial to our continued development. In 2010 67.4% of the world's electricity was produced using one of the 3 main fossil fuels: oil, coal and natural gas (World Energy Council, 2013). During that same year, the world generated around 21,432 TerraWatthours of electricity. Of that, 4,757 TerraWatthours of electricity came from natural gas, 986 TerraWatthours from oil, and 8,701 TerraWatthours from coal (U.S. Energy Information Administration, 2014).

The world population is on the rise and is expected to keep increasing. This also means the human demand for energy and electricity is also expected to increase. Because of the limited characteristic of fossil fuels, as the world population increases and the amount of fossil fuels available slowly depletes, it will no longer be possible to continue to heavily depend on fossil fuels as our main source of energy.

Furthermore, the use of fossil fuels to produce energy has also been shown to be the primary source of CO_2 emissions (United States Environmental Protection Agency, 2011). The effect of greenhouse gas (GHG) emissions on climate change has been proven time and time again and although the magnitude of this effect is uncertain, to be prudent, non-fossil fuel energy technologies should be developed and utilized. Since the beginning of the Industrial Revolution around the world, the use of fossil fuels to produce energy has contributed to a 40% increase in the levels of carbon dioxide in the atmosphere (Blasing, 2014).

Fortunately, the use of fossil fuels is not the only way to generate electricity. Power can also be generated using renewable sources that are naturally restored or nuclear sources. Renewable sources include wind, tides, waves, geothermal heat and sunlight.

The International Energy Agency (IEA) predicts that “by 2050, nearly 50% of global electricity could come from renewable energy sources” (IEA, 2015). A shift towards a higher penetration of renewable energy sources can already be observed around the world. In 2013, for example, 22% of the global electricity was generated using renewable sources of energy (IEA, 2015). With the growing penetration of renewable energy in the generation mix, the variability and unpredictability of the energy supply mix is also bound to increase. When dealing with traditional energy sources, such as coal, natural gas and oil, the exact amount of power generated can be predicted with very little error. Excluding unexpected machine breakdowns, operators usually have complete control over how much electricity they are producing within a certain hour. This is because operators are able to start up, shut down, and adjust traditional generator outputs depending on given generator restrictions and the demand for power. In such a power system, the major cause of variability occurs due to the changing demand for electricity during the day and across the year.

When renewable power sources are also included in a power system, decisions across different planning horizons will be impacted. The major reason behind this is the intermittency of renewable generation which occurs due to a combination of two characteristics: limited control of variability and low predictability. Because operators have no control over when the wind blows or when the sun shines, a reliability issue arises when high levels of renewable sources make up the electricity generation mix. This has in turn increased the complexity of power system problems and has changed the manner in which operators plan generation.

In the unit commitment short term planning problem, operators attempt to determine which generators to turn on and when, in response to varying demand. In this kind of model decisions are usually made on an hourly basis (every hour) for a particular day or week to reflect adequate short term details within the system. Ramping constraints in such a model are added to allow operators to restrict what generators have the capability to ramp up or down to meet changing demand. Note that a generator's ramping capability is how fast it is able to increase or decrease its output (measured in MW/hr). The ramping capabilities also help deal with the variability associated with renewable sources of energy. For example, when wind levels drop, system operators must be able to ramp up other generators in the system to the appropriate production level to meet the sudden decrease in wind production while meeting a variable demand level.

In medium and long term planning models however, short term details have traditionally been overlooked. Because attempting to model years in an hourly fashion similar to that of a unit commitment model quickly becomes computationally prohibitive, different methods to simplify and approximate operation details are adopted in practice. In the long term capacity planning problem, operators attempt to make decisions years ahead of time on what generator types to invest in in order to meet future electricity needs. In such a model an approximate electricity demand forecast is used. Furthermore, short term generation variables such as ramping capabilities, start up and shut down limitations and minimum loads are ignored and reserved for short term planning models. Such simplified long term models have historically yielded good results due to the straightforward nature of operational details that are mainly related to fairly predictable demand patterns. With the increasing penetration of less predictable renewable energy sources however, the fluctuations in net demand (total electricity demand minus amount supplied through renewable energy sources) that needs to be met using traditional energy sources is also expected to increase. Operators of a system will therefore need to respond to higher variability on both the demand and supply side of the system. Generators within a system will also need to have the ability to meet such variability and will potentially require higher ramping capabilities in order to respond to the intermittency of renewable energy sources. The work in this thesis attempts to illustrate that capturing short term constraints, such as the ramping constraints originally found in unit commitment models, in the long term capacity expansion model may result in a more realistic power output and capacity mix when planning future generation investments.

The thesis is organized as follows: section 2 reviews the literature on the area of research; section 3 introduces the traditional capacity expansion model and the new proposed constraints; section 4 considers 2 experiments based on provincial data from Ontario and demonstrates the difference in results between the basic model and the new proposed model modification; finally, section 5 presents a brief summary and some areas of future research.

2 Literature Review

As different policies around the world drive an increase in investment in renewable energy sources, the way traditional electricity systems operate has also been changing. In an attempt to address the observed changes and assess the challenges of incorporating large amount of wind and solar technologies, a wide variety of studies have been undertaken (e.g. DOE 2008, GE Energy 2010, IESO 2006). Furthermore, to meet the need to account for the renewable sources from a planning perspective, many attempts have been made in different areas of the literature. Some of these are discussed next.

Both short term and long term planning horizons are impacted when renewable sources are introduced into a power system. Tuohy et al. (2009), for example, consider the short term unit commitment problem in their paper. The authors attempt to account for significant wind penetration into the system and find doing so results in less costly, better performing results. This thesis however does not consider short term models but instead focuses on the long term capacity expansion problem.

Capacity expansion models in the power industry help make generation investment decisions based on the demand for electricity. The models designed are able to build a complete power system from scratch or update an existing one to account for the changing needs across a particular time frame. Several types of capacity expansion models exist including simulation (e.g. Short, Ferguson and Leifman, 2006) and optimization models. Van Beeck's work (1999) investigates different energy model types and classifies them according to their purpose, model structure, analytical approach, mathematical approach (e.g. linear programming vs. mixed integer programming), geographical and sectoral coverage, time horizon, and model methodology (e.g. optimization vs simulation). This thesis's focus is on capacity expansion using a linear programming optimization model.

One of the simplest ways to account for renewable energy generation in a long term planning model, such as the capacity expansion model, is to substitute the demand parameter by net demand. Net demand, as defined elsewhere in this thesis, is simply the demand minus the amount of power produced using renewable energy sources. This approach can be observed in the work done by Caramanis, Tabors, Nochur, and Schweppe (1982) and Nicolosi (2012). Nicolosi, for instance, subtracts the renewable generation from the load (demand), and then uses a dispatch and capacity expansion model to optimize the remaining traditional generation. While this method is effective, and is used in this thesis, it is insufficient on its own when the penetration of renewables sources into the system becomes very high.

Capacity expansion models typically have little to no operational details included in the modeling due to the high computational requirements such details would entail. It is therefore common to observe an aggregation of hourly time periods into larger annual time blocks or the load variations over the day and seasons being approximated by load levels in a load duration curve (e.g. Murphy and Smeers, 2005). With the loss of some of the operational details, the model gains the capability to span over longer periods of time while remaining computationally tractable. In such approaches however, chronological information between consecutive hours, which may be important when considering renewable sources, is lost. Wogrin, Duenas, Delgadillo and Reneses (2014) introduce an alternative novel method that still allows the modeller to incorporate chronological information. While the methods used by Wogrin, Duenas, Delgadillo and Reneses were shown to be effective, they remain relatively complex. This thesis therefore opts to use the traditional load duration curve but attempts to restore some chronology using added constraints which is a much simpler and straightforward method to use.

Because of the more pronounced variability in the net demand, the system potentially requires a higher ramping capability to be able to more quickly vary its output. It is therefore necessary to restore these operational details into the model. These details have traditionally been included in short term models only, such as the aforementioned unit commitment model. Long term models, as mentioned, do not typically include such features due to the potential computational burden in solving them. Palmintier and Webster (2011) proposes a method that combines the short term details found in unit commitment models with the long term capacity expansion model. Palminitier however uses a chronological time frame and distinguishes between individual plants which could still lead to a large problem size. This thesis, on the other hand, sticks with the simple load duration curve to represent net demand, and merges all similar generating plants into a single generation type to maintain tractability.

3 The Mathematical Model

The capacity expansion problem involves a process of providing new resources (such as facilities) over time to satisfy a time varying demand. Power generation companies, like organizations in other industries, also face capacity expansion decisions where they attempt to increase their generation capacity. A decision support model attempts to select a mix of power generators that would minimize the total costs (fixed and variable costs) while satisfying the variable demand for power over a set time horizon (typically around 20 years). Different generators have different variable and fixed costs related to the type of fuel used, operations and facility costs among other things. Furthermore, the generators also have limitations such as whether or not they are available. For example, there is a physical limitation on how many hydro plants (generators that produce electricity through the use of the gravitational force of flowing water) can be built due to the finite nature of water sources that are able to generate hydropower.

As stated earlier, and as will be demonstrated next, the traditional capacity expansion model, in its simplest form, is very straightforward and does not attempt to model any details beyond simplified approximations of generation demands and costs. This chapter first presents the generation capacity expansion model in this basic form, then presents the new constraints and changes recommended to capture short term sequential dynamics that are increasingly necessary to consider as the amount of renewable penetration in the system increases, and the amount of variability increases with it.

3.1 Basic Capacity Expansion Model

The simple generation expansion model is a linear program that attempts to minimize total fixed and variable costs subject to constraints related to supply/demand balancing, capacity and depreciation. The model described is shown in equations 1 – 6 and is explained in detail in the next sections. The variables and indices introduced will also be summarized in Appendix A. Note that decision variables and parameters are represented using capital letters and small letters respectively.

$$\textbf{\textit{Minimize}}_{X,K,I} \qquad \sum_{i,t,s}\left(c_{i,t}h_s X_{i,t,s}\right)+\sum_{i,t}\left(inv_{i,t}I_{i,t}\right) \tag{1}$$

Subject To:

$$\sum_{i}\left(h_s X_{i,t,s}\right)=d_{t,s} \qquad \forall\ t,s \tag{2}$$

$$K_{i,t} \geq X_{i,t,s} \qquad \forall\ i,t,s \tag{3}$$

$$K_{i,t} = exK_{i,t} + \sum_{\max(1,t-age_i+1)}^{t} I_{i,t} \qquad \forall\ i,t \tag{4}$$

$$\sum_{t} K_{i,t} \leq maxcap_i \qquad \forall\, i \tag{5}$$

$$X_{i,t,s}, I_{i,t}, K_{i,t} \geq 0 \tag{6}$$

3.1.1 Model Indices

Three main indices were used in the model introduced and are explained in sections 3.1.1.1 – 3.1.1.3.

3.1.1.1 Generation Type

Unlike the majority of the capacity expansion models found in the literature, the model presented here uses no binary variables to represent new potential generating capacities. Instead, continuous variables are used, as will be demonstrated in section 3.2, that group all new potential capacities into a single variable. For example, instead of representing 10 different potential generators as generators 1 to 10 and investing in them or not using binary variables, generators are aggregated according to their type and are represented using the index i in different continuous variables. Generation types can vary from renewable power generation (such as wind and solar) to traditional generation types (such as gas and nuclear).

3.1.1.2 Year

Capacity expansion models are long term by nature and typically span over 20 years. In this model formulation, the year index is represented using t.

3.1.1.3 Demand Block

Assuming the quality of data is equally accurate, when attempting to model a situation that varies over time, the smaller the time segments considered, the more accurate the result. For example, a model considering variations per minute, would be more accurate than one modeled on an hourly basis, which in turn is much more accurate than one modeled on an annual basis. When looking at power systems in particular, different types of models choose the time granularity depending on the level of detail necessary. In short term models for example, such as the unit commitment model, power demand is represented on an hourly basis. When considering a long term model such as the capacity expansion model however, attempting to model demand on an hourly basis quickly becomes computationally cumbersome. A very common approach is representing power demand using what is commonly referred to as “demand blocks”. These demand blocks are obtained by approximating a load duration curve using a step function. Note that a load duration curve is the hourly power demand in a specified time period (typically a year) rearranged from the highest demand to lowest. An example load duration curve displaying 2007 Ontario data obtained from the IESO is shown in figure 1.

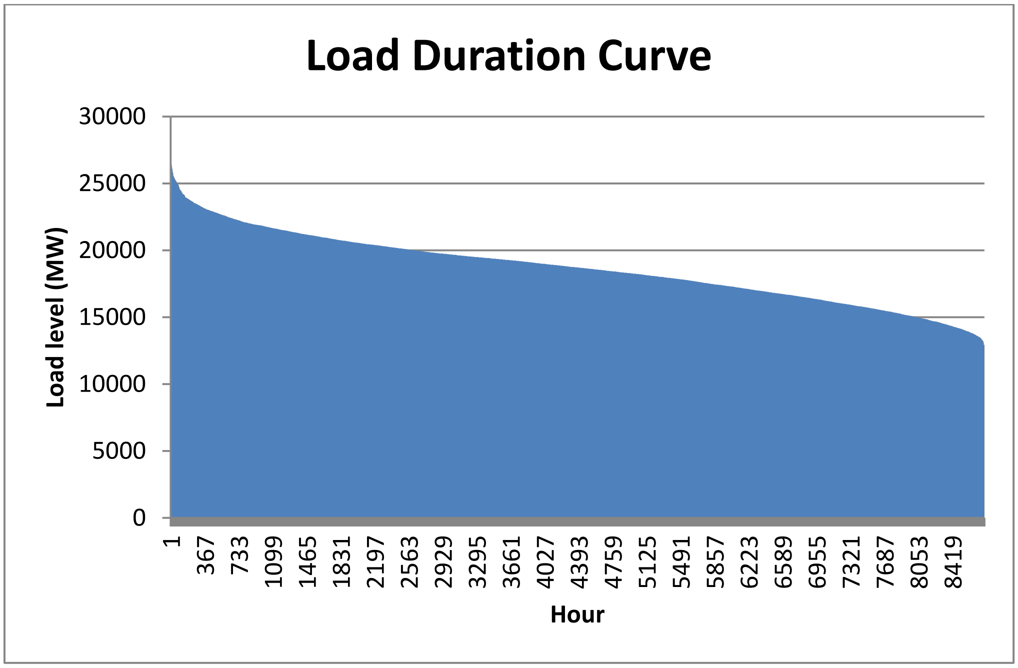

Figure 1 - Load Duration Curve

Approximating and discretizing the load duration curve using demand blocks can be done horizontally or vertically (Sherali, 1982) as shown in figure 2. In the horizontal approximation, the load duration curve is segmented horizontally with each segment allocated a particular capacity. On the other hand in a vertical approximation, the curve is divided vertically with each segment being a specified number of hours. Because each segment (demand block) has a demand level (typically MW) and duration (hours), the area of the block is the power demand (typically MWh). Because the vertical approximation retains some notion of sequentiality that is necessary to define the ramping constraints detailed in later sections, this thesis opts to use it in favor of the horizontal approximation.

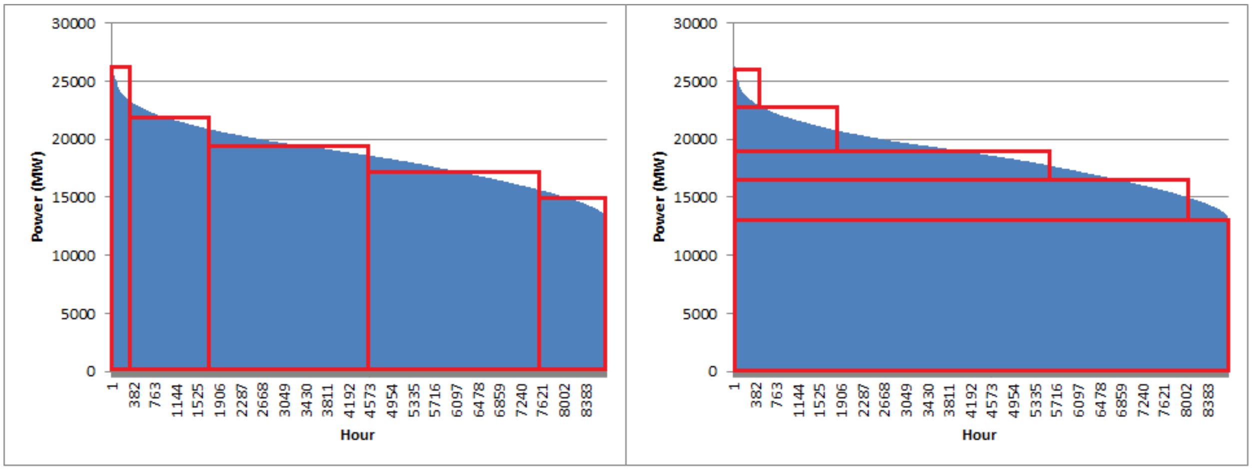

Figure 2 - Vertical vs. Horizontal Approximation. Adapted from Sherali et al.

A typical vertical approximation of the load duration curve results in three demand blocks usually labeled as “base”, “intermediate” and “peak” to represent three different load levels. It is however up to the modeller to decide how many demand blocks to utilize depending on the needs. The demand blocks are indexed using $s = 1 \ldots S$ in this paper.

3.1.2 Decision Variables

Three main decision variable groups were used in the model introduced and are explained in sections 3.1.2.1 – 3.1.1.3.

3.1.2.1 Power Output

The variable $X_{i,t,s}$ is used throughout this paper to represent the level of power output in megawatts (MW) produced by the of generators of type i during demand block s of year t.

3.1.2.2 Total Capacity

The decision variable $K_{i,t}$ quantifies the total capacity of generation type i available during year t, i.e. the maximum power than can be produced. This includes the capacity from existing generators and new generators invested in and constructed that particular year. The capacity is measured in MW.

3.1.2.3 New Capacity

A decision variable $I_{i,t}$ is used to identify the level of new capacity (MW) of generation type i invested in and constructed during year t.

3.1.3 Parameters

Five different parameter groups were used in the model introduced and are explained in sections 3.1.3.1 – 3.1.1.5.

3.1.3.1 Demand Forecast

The net demand for energy, $d_{t,s}$, modeled in this paper is a parameter estimated prior to beginning the analysis for every demand block s during year t and is measured in MWh. Future energy demands have been found to be strongly linked to economic, population and production growth (Department of Natural Resources, 2013), and forecasts are often based on projections of historic data. Provincial system operators typically prepare future demand and energy outlook documents that outline the assumptions, methods and processes taken to assess the future provincial energy requirements (AESO, 2008). After obtaining a forecast for future power demand, to find the net demand, $d_{t,s}$, non-dispatchable renewable power production should also be approximated and then subtracted. This method of using net demand instead of demand has traditionally been used in an attempt to account for the introduction of non-dispatchable power sources (technologies that depend on resources that produce power at a rate uncontrollable but the system operator) such as solar and wind, as can be seen in (Caramanis et al., 1982).

3.1.3.2 Hours

The parameter h_s, measured in hours, simply specifies the duration of a demand block s. As was seen earlier, because each demand block has both a length of time (hours) and a power demand (MW), it is necessary for the modeller to specify the length of each of the demand blocks.

3.1.3.3 Variable Costs

The present worth of the variable cost $c_{i,t}$ per unit of generation is a parameter measured in $/MWh for each generator i during year t. The variable costs could include costs related to operation and fuel usage.

3.1.3.4 Investment Costs

The present worth of investment in new capacity of generation type i during year t is a parameter represented using $inv_{i,t}$ and measure in $/MW. This cost is allocated per each new unit of capacity.

3.1.3.5 Existing Capacity

The parameter $exK_{i,t}$ measured in MW represents existing capacity of type i during year t. This parameter accounts of all generation capacities built before the start of the model and represents how much of them still exists after their depreciation over the years. For example, at time = 0 (one period prior to the start of the model), generators of type i and a particular capacity existed. To recognize that generators depreciate over the years, $exK_{i,t}$ states how much of this existing capacity remains over the model's time frame.

3.1.4 Objective Function

The capacity expansion objective function as shown, (1) attempts to minimize the total costs associated with both variable and investment costs.

The first part of the objective function ($\sum_{i,t,s}(c_{i,t}h_sX_{i,t,s})$) allocates a particular variable cost (in in present worth dollars) for each unit of power produced. Note that $X_{i,t,s}$ is a production level in MW and must be multiplied by the number of hours to obtain the energy output. This goes back to the vertical demand block approximations of a load duration curve where each demand block has a power level (MW) and a length of time (hours) thereby dictating that the demand block's area is the energy output in MWh. On the other hand the second part of the objective function ($\sum_{i,t}(inv_{i,t}I_{i,t})$) assigns a cost for every new unit of power capacity to be invested in.

3.1.5 Constraints

This section explains the constraints used in the capacity expansion model.

3.1.5.1 Demand Balance

The demand balancing constraint (2) is a straightforward demand = supply formula that basically forces the power system to produce enough power to meet the power demand. The left hand side represents the amount of energy produced by all generators in a particular year *t* and demand block *s* (MW × hr) which is equated to the approximated demand per year and demand block (MWh).

$$\sum_i \left(h_s X_{i,t,s}\right) = d_{t,s} \qquad \forall\ t, s \tag{2}$$

3.1.5.2 Capacity Constraints

There are 3 different types of capacity constraints in our simple capacity expansion model. The first one, (3), restricts the level of power production to be less than the total available generator capacity in a particular year. This constraint basically says that you must have enough capacity of each generator in a particular year to be able to produce power at the specified level for that generator and year. Because both sides of the constraint are in MW, no unit balancing is necessary.

$$K_{i,t} \geq X_{i,t,s} \qquad \forall\ i,t,s \tag{3}$$

The second capacity constraint, (4), ensures that the total capacity $K_{i,t}$ includes both capacity built prior to the beginning of the model after depreciation ($exK_{i,t}$), and all new investments until the current year t ($\sum_{\max(1,t-age_i+1)}^{t} I_{i,t}$). Note that age_i is the approximated life of the generator. For example, nuclear generators are found to last 30 years on average.

$$K_{i,t} = exK_{i,t} + \sum_{t'=\max(1,t-age_i+1)}^{t} I_{i,t'} \qquad \forall\ i,t \tag{4}$$

The final capacity constraint, (5), accounts for maximum limitations related to physical generator restrictions. For example, hydro generators have geographical restrictions related to where they can be built. This implies a maximum limitation on how much new hydro capacity can be constructed. In this constraint, the parameter $maxcap_i$ is an estimation of how much capacity is available of a particular generation type at the beginning of the model time frame.

$$\sum_{t} K_{i,t} \leq maxcap_i \qquad \forall\, i \tag{5}$$

3.2 Incorporating Short Term Ramping Constraints

Because of the current inability to store electricity on a large scale in power systems, the power demanded and power supplied must be constantly balanced and equated throughout the day (Kirby and Milligan, 2005). This generates an important need for generators to be able to adjust output as net demand fluctuates and be capable of "load following" (Kirby and Milligan, 2005).

As explained earlier in this paper, with the expected increase of renewable energy sources into the power systems, and along with it the increase of variability and decrease in predictability, it becomes important to attempt to ensure that, in the long term, the built power generation systems have the capability to meet future demands while being able to adjust generation to account for variable increases and decreases of renewable power produced. The first two additional constraints added to the model and explained in section 3.2.1 ensure that the system has the ramping capability (how fast it can increase or decrease its output) to be able to follow the fluctuations in net demand. However, because generation ramping is dependent on sequential information that is lost when demand blocks are used, nine more constraints, explained in section 3.2.2, are included to add some chronological sense to the model and support ramping. Finally, one of the capacity constraints found in the original capacity expansion model is also altered to account for the new parameters added.

3.2.1 Total Ramping Constraints

Because renewable sources, such as wind, produce power with very little predictability, when a sudden drop or surge in renewable power generated is observed, the power generation system must be able to ramp up or down fast enough to meet the change in net demand. Note that as mentioned previously, net demand = demand in MW – renewable power generated in MW. This implies that a drop in renewable sources increases the net demand, and therefore other traditional generators (such as gas turbines or nuclear power plants) must increase their output to meet this increase. On the other hand, a surge in renewable sources reduces net demand thereby decreasing the amount of power demand traditional generators must meet.

Constraints (7) and (8) are added to the capacity expansion problem outlined in the previous section and account for the power system's ramping capability (is able to ramp up and down) to meet the net demand's fluctuations.

$$\sum_i up_i K_{i,t} \geq rup_{t,s} \qquad \forall t,s \tag{7}$$

$$\sum_i dn_i K_{i,t} \leq rdn_{t,s} \qquad \forall t,s \tag{8}$$

3.2.1.1 Generator Ramping Parameters

A system's ramping capability is the sum of the ramping capabilities of all the generators that are on during the time period *t*. That being said, the parameters up_i and dn_i are generator related and represent the maximum ramp up rate and maximum ramp down rate of a particular generator type respectively. This is measured in fraction per minute. To illustrate why the "fraction per minute" unit of measurement is used, consider a single generating unit *j* (unlike the aggregation of similar generators' output into a single variable as is done in the rest of this paper) with a maximum ramping capability, a_j, measured in MW/min, and a capacity $Capacity_j$, in MW. The single generator's maximum ramping capability per unit of capacity would then be calculated as $\frac{a_j}{Capacity_j}$. Now consider the class of many similar generators of the same type, *i*, each with ramping capability a_j, capacity $Capacity_j$, and total available capacity of the whole class *i* of $K_{i,t}$. The total ramping capability of all generators in class *i* depends on how much of the capacity of type *i* is available during period *t*. It is therefore reasonable to model the total ramping capability of all generators in class *i* as $max(\frac{a_j}{Capacity_j})K_{i,t}$. In our model, parameters up_i and dn_i are estimated using $\frac{a_j}{Capacity_j}$, from information about a single generator of type *i*, consequently, the system's upwards and downwards ramping capabilities are represented using $up_i K_{i,t}$, and $dn_i K_{i,t}$ respectively and making up the left hand side of the ramping constraints.

3.2.1.2 Demand Ramping Parameters

On the right hand side of constraints 7 – 8, are parameters $rup_{t,s}$ and $rdn_{t,s}$ which represent the maximum rate of change of net demand in period t and demand block s surge and drop respectively, measured in MW/min.

In summary, the constraints shown in equations 7 – 8 ensure that the systems ramping capability is greater than the maximum amount of ramping done by the net demand. This ensures that the system can adequately increase or decrease the supply of power to meet the drops and surges in net demand that are caused by both the regular fluctuations in power usage and the fluctuations caused by the intermittency of renewable power sources. Note that the first equation is a greater than equality, while the second is a less than equality to account for the negative signs of dn_i and $rdn_{t,s}$ that occur due to the decreasing nature of each.

3.2.2 Sequencing Constraints

The ramping history of a particular generator can be determined by observing a generator's behaviour. Hourly generator output data, for example, can be analyzed and the hour's ramping can be conservatively approximated by subtracting one period's output from the next. Evidently, a generator's ramping, and therefore the ramping constraints, are chronologically dependent.

In an attempt to reduce the problem size, demand blocks, defined by an output level and time duration, served as an approximation for the load duration curve in the simple capacity expansion model outlined. Unfortunately, using demand blocks has the disadvantage of the loss of sequential information when hours are reordered from largest to smallest output to form the load duration curve used. In an attempt to overcome the loss of sequential details new constraints have been formulated and added to the model as shown in equations 9 – 14. To illustrate these constraints and how they relate to the model it is assumed from here on out that *s* is equal to three demand blocks chosen to represent three different levels of demand: peak (highest power demand), intermediate (medium power demand) and base (lowest power demand). This is a common choice for *s*, but the model can be changed and adjusted to account for more or fewer demand blocks.

$$up_i * 60 * rBP * K_{i,t} + X_{i,t,base} \geq X_{i,t,peak} + BP_{i,t} \quad \forall i,t \tag{9}$$

$$up_i * 60 * rBI * K_{i,t} + X_{i,t,base} \geq X_{i,t,inter} + BI_{i,t} \quad \forall i,t \tag{10}$$

$$up_i * 60 * rIP * K_{i,t} + X_{i,t,inter} \geq X_{i,t,peak} + IP_{i,t} \quad \forall i,t \tag{11}$$

$$dn_i * 60 * rPI * K_{i,t} + X_{i,t,peak} \leq X_{i,t,inter} \quad \forall i,t \tag{12}$$

$$dn_i * 60 * rPB * K_{i,t} + X_{i,t,peak} \leq X_{i,t,base} \quad \forall i,t \tag{13}$$

$$dn_i * 60 * rIB * K_{i,t} + X_{i,t,inter} \leq X_{i,t,base} \quad \forall i,t \tag{14}$$

3.2.2.1 Ramping Time Parameters

These six sets of constraints dictate how long particular generators have to ramp from one level to another in a single day. To illustrate how these constraints work we will consider a typical summer day in Ontario as shown in figure 3.

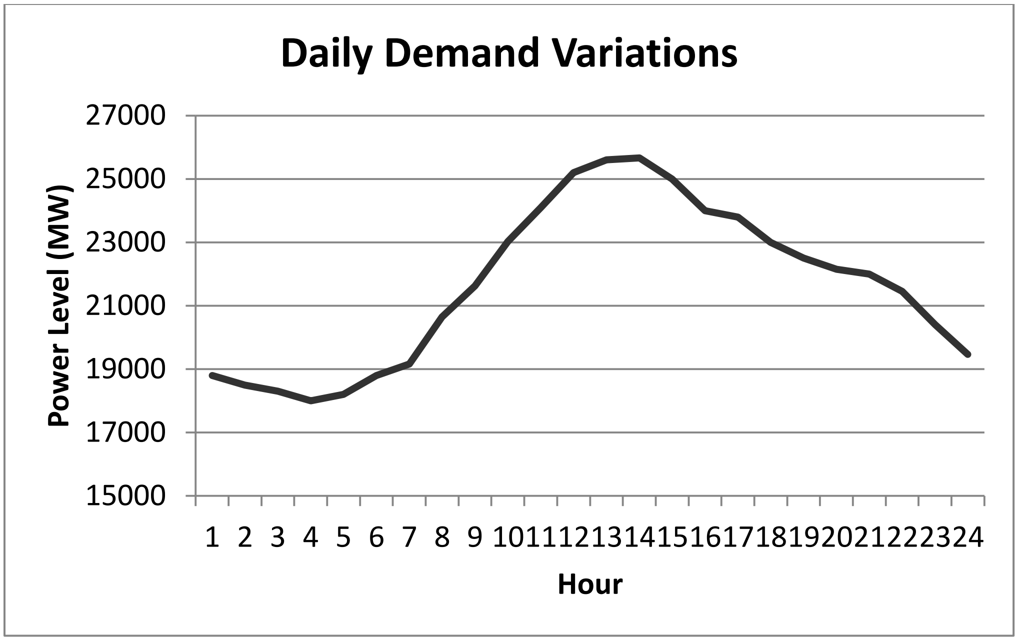

Figure 3 - Daily Demand Variations

It is clear from this figure that a single peak occurs between the 12th and 15th hour. On the other hand, the lowest demand seems to occur during the first 6 hours of the day while the rest of the day can be considered to be of "medium" or intermediate demand. If three demand blocks were to be created for the day, the result would resemble figure 4. Note that the green block is 12 hours long and represents the base demand period, the orange block is 8 hours long and represents the intermediate demand block, and the red block is 4 hours long and represents the peak demand period.

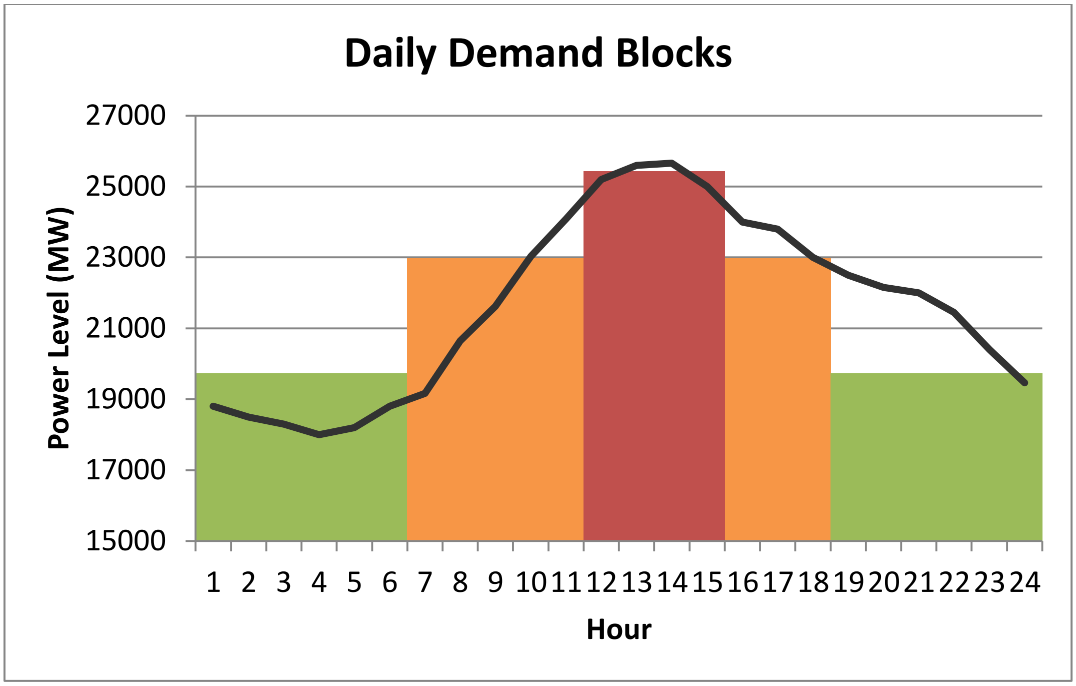

Figure 4 - Daily Demand Blocks

With the example in figure 4 in mind, what the six constraints in equations 9 – 14 attempt to do is to dictate how many hours a particular generator group has to move from one power output level to another and restrict its output accordingly. That being said, the following parameters are defined:

- rBP: is the number of hours a generator has to ramp up from base output level to peak output level.
- rBI: is the number of hours a generator has to ramp up from base output level to intermedia output level.
- rIP: is the number of hours a generator has to ramp up from intermediate output level to peak output level.
- rPI: is the number of hours a generator has to ramp down from peak output level to intermediate output level.

- rPB: is the number of hours a generator has to ramp down from peak output level to base output level.
- rIB: is the number of hours a generator has to ramp down from intermediate output level to base output level.

In the example of figure 4, rBI is 12 hours (end of hour 18 to the end of hour 6 of the next day), i.e.; the generators have 12 hours to adjust their output level from the base level to the intermediate level. Furthermore, because there's no direct movement from the base demand block to the peak demand block and vice versa in this example, the relevant constraint, i.e., constraints 9 and 13 are omitted from the model of this example.

It is worth noting at this point that the method illustrated here to choose values for parameters *rBI, rIP, rPI, rIB, rBP* and *rPB* is only an illustrative method. The proper choice of these parameters requires expert judgement and further work. As will be illustrated later in this work, the selection of these parameters is crucial to the success of the model and obtaining viable results.

To further demonstrate how constraints 9 – 14 function, consider equation 12. The first part of this constraint ($dn_i * 60 * rPI * K_{i,t}$) changes the maximum ramp down rate from fraction/min to fraction/hr by multiplying by 60. Then this value is further multiplied by the capacity $K_{i,t}$ to yield a value related to how much the generators of type *i* can ramp down in an hour (in MW/hr). Finally, this is then multiplied by the number of hours the generator has to ramp down from the peak to intermediate production level to obtain the total maximum amount in MW generator group of type *i* can drop from the peak to intermediate demand block. Because this is a drop in production level, this part of the constraint will yield a negative value that is then subtracted from the output level during the peak demand block, $X_{i,t,peak}$. The constraint dictate that the output level during the intermediate period ($X_{i,t,inter}$) cannot be smaller than the output level during the peak demand block, $X_{i,t,peak}$, after is has been reduced by the maximum amount (in MW) that the generator can drop by given the time restriction rPI.

3.2.2.2 Renewable Variation Parameters, Variables and Constraints

Three more variables, $BP_{i,t}$, $BI_{i,t}$ and $IP_{i,t}$ also appear in the six constraints (equations 9 – 14). These variables, in addition to the parameters and constraints shown in equations 15 – 17, account for sudden drops in renewable power generation occurring just when demand is increasing. Unlike the wind output accounted for in the Net Demand calculations, these drops in wind attempt to also take into account a worst case scenario where no wind blows during this time across the province. Note that we make an assumption that power systems have the ability to curtail (not accept into the system) excess power generated by renewable sources such as wind, therefore spikes in renewable generation do not need to be considered.

$$bp_t = \sum_i BP_{i,t} \qquad \forall t \tag{15}$$

$$bi_t = \sum_i BI_{i,t} \qquad \forall t \tag{16}$$

$$ip_t = \sum_i IP_{i,t} \qquad \forall t \tag{17}$$

$BP_{i,t}$, is a variable that indicates the level produced by each generation type *i* during *t* to make up for the change in wind from the base to peak demand block bp_t which is a parameter of the model. Similarly, $BI_{i,t}$ and $IP_{i,t}$ dictate how much different generator groups will need to produce to make up for the changes in wind from base to intermediate (bi_t) and intermediate to peak (bi_t) respectively. The 3 constraints (equations 15 – 17) then ensure that enough power is produced to account for the changes in wind. Furthermore, the capacity constraint (3) from section 2, is modified as follows to ensure enough capacity is available to also meet this new demand type resulting from sudden drops in wind production.

$$K_{i,t} \geq X_{i,t,s} + BP_{i,t} + BI_{i,t} + IP_{i,t} \qquad \forall\ i,t,s \tag{18}$$

4 Numeric Experiment

In this chapter the proposed capacity expansion model with ramping and time sequencing constraints is tested using data obtained pertaining to Ontario. The data used is gathered from three main sources: the Integrated Power System Plan (IPSP) published by the Ontario Power Authority in 2007 (OPA, 2007), the Long-Term Energy Plan (LTEP) issued by the Ontario government in 2013 (Government of Ontario, 2013), and the work done by Mehrdad Pirnia on capacity pricing in electric generation expansion (Pirnia, 2009).

Two different experiments are completed to highlight two important points: first, by introducing ramping and time sequencing constraints into the capacity expansion model a change in investment plans is observed and found to yield more appropriate results; second, when considering the time sequencing constraints it is imperative that the parameters related to how long a generator has to ramp from one demand block to another are selected carefully.

4.1 Indices

This section introduces the indices used in the experiments conducted.

4.1.1 Time Period

Due to the lack of more recent data sources, the model will consider a 21 year time frame that starts in 2007. The index t for each year therefore ranges from 1 to 21 representing years 2007 until 2027.

4.1.2 Demand Blocks

The example experiments consider three distinct demand blocks s: peak, intermediate and base.

4.1.3 Power Generation Types

There are different methods of generating the power demanded. The index i represents each available type of generation currently built or available to invest in. The example experiment considers the following different types of generations: nuclear generators, coal generators, simple cycle gas turbines, combined cycle gas turbines, small hydro generators, medium hydro generators, large hydro generators, and biofuel generators. A distinction is made between existing generation capacity and new generation capacity by labeling existing generation with an "Ex" prefix. For example, Nuclear generation capacity that exists at the start of the model falls under "ExNuclear" and not "Nuclear". Note that renewable sources like wind and solar are only considered as existing sources because as their future output is accounted for in Net Demand (total demand minus power generated through renewable energy sources). This means the model makes no suggestions on how much renewables to invest in as that is assumed to be a decision completed separately outside the realms of this model. Furthermore, this experiment only considers wind production as a renewable energy source for simplification purposes. Another thing to keep in mind is that although coal generators are considered in the model, because they have been phased out of Ontario as of 2014, the coal generators are only available as existing generators while no new investments in the area are allowed in the model.

4.2 Parameters

4.2.1 Net Demand

The net demand forecast (MWh), $d_{t,s}$, is a parameter needed for each year t and demand block s.

To estimate this parameter, the following data were used:

- Ontario's power demand for each hour of the day for 2007 (MW), obtained from the "Hourly Ontario and Market Demands" report published by the Independent Electricity System Operator (IESO), the body "responsible for the day-to-day operation of Ontario's electrical system" (IESO, 2015).
- The average annual demand growth rate (%) obtained from "The Load Forecast – IPSP Reference Energy and Demand Forecast" document published by the Ontario Power Authority (OPA).
- The annual amount of power generated using wind generators from 2007 to 2012 (MWh), obtained from the "Hourly Wind Generator Output" report published by the IESO.
- The forecasted amount of annual power generated using wind generators available for years 2013 to 2027 (TWh), obtained from the Long Term Energy Plan (LTEP) published by the OPA. (OPA, 2014)

In order to calculate the forecasted net demand for 2007 – 2027, the first thing done was to use the 2007's historical hourly Ontario demand as a starting point. A load duration curve (shown in figure 5) was created and the three power levels for peak, intermediate and base were used as the starting point for the 20 year demand forecast for each demand block.

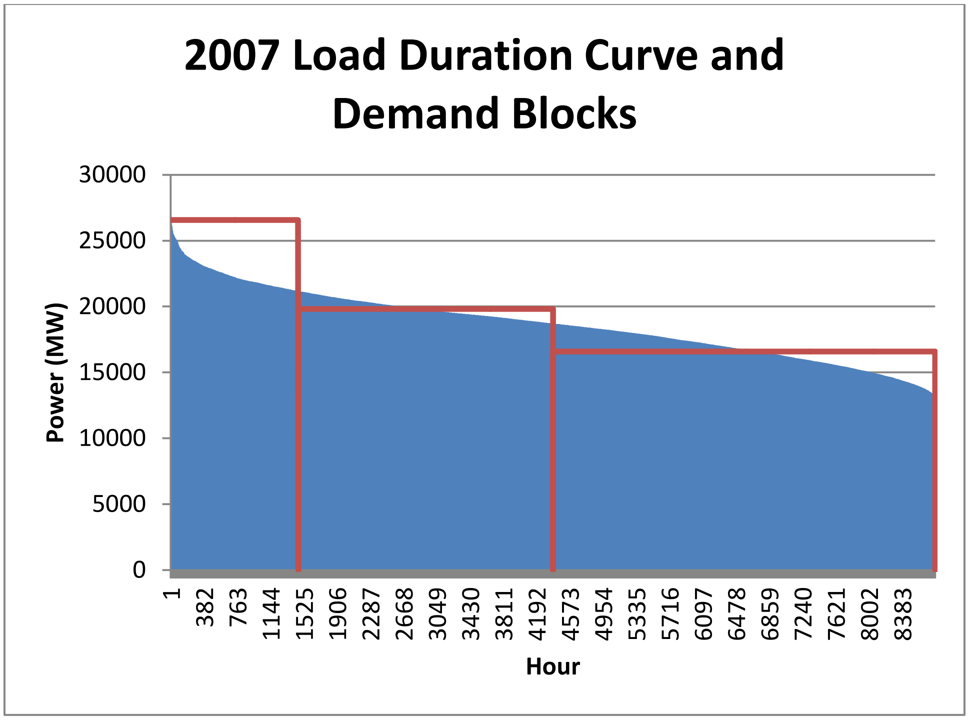

Figure 5 - 2007 Load Duration Curve and Demand Blocks

The average annual demand growth is found to be 1.2% in the IPSP. Accordingly, using the 2007 power demand for each demand block, the demand for each demand block for the following 19 years is calculated (MWh).

To find the net demand $d_{t,s}$, wind production needs to be accounted for and subtracted from the forecasted demands. With this in mind, the wind data collected from the OPA and IESO is used and is subtracted accordingly to finally yield the needed parameters for the model. Note that due to the fact that the OPA wind forecast started at the year 2013, actual historical wind data from the IESO was used for the years 2007 to 2012. The final net demand values are visualized in figure 6 and table 3 in Appendix B.

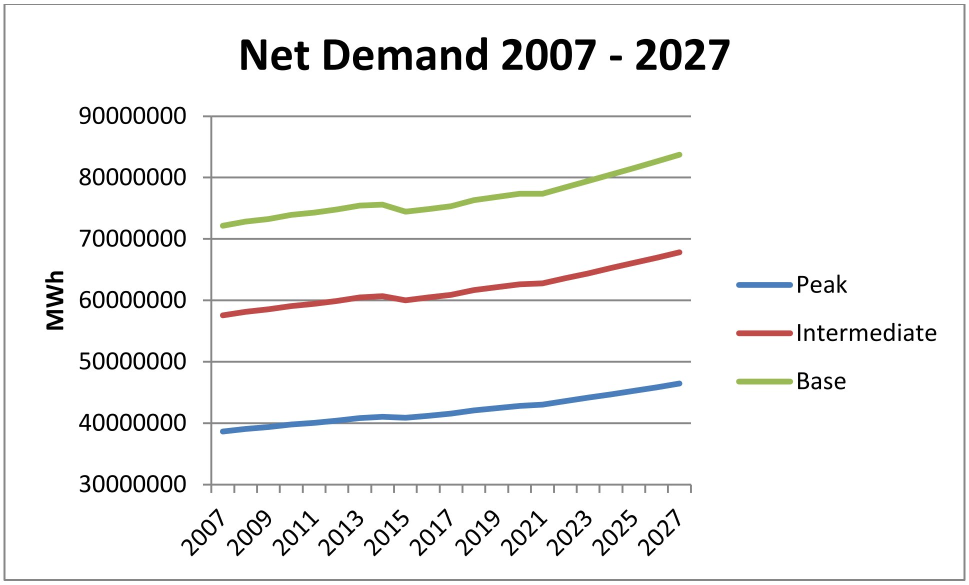

Figure 6 - Net Demand 2007 - 2027

4.2.2 Hours of year for demand block s

The parameter h_s is total hours of the year allocated to each demand block. The values used in this example are based on the work done and data collected by Pirnia (Pirnia, 2009) as shown in Table 1. Note that these demand blocks correspond to the red blocks shown in figure 5.

Demand Block	Hours Allocated
Peak	1460
Intermediate	2920
Base	4380

Table 1 - Hours Allocated to Demand Block

Another way of looking at the hour allocations per demand block is on a daily basis. The parameters chosen in table 1 imply that each day in our model has 4 hours of peak demand, 8 hours of intermediate demand and 12 hours of baseload demand.

4.2.3 Variable Costs

The example experiment completed assumes two kinds of variable costs: operating costs and fuel costs. The operating costs include things such as raw materials, labour, maintenance etc. On the other hand, the fuel cost is simply the cost of the actual fuel needed for the generator, for example the gas needed for the combined cycle gas turbines.

Since this is a long term model over several years, it is important to account for the growth of costs over time. Therefore, it is necessary to calculate the present worth of the variable cost. This calculation, shown in equations 19 – 21, is based on the work done by Pirnia (2009). Note that *r* is the interest rate, $FCgrowth\_rate_i$ is the growth rate of the fuel cost of generator *i*, and $OCgrowth\_rate_i$ is the growth rate of the operating cost of generator *i*.

$$Present\ worth\ of\ \ fuel\ cost_{i,t} = \frac{fuel\_cost_i * \left(1 + FCgrowth\_rate_i\right)^{t-1}}{\left(1+r\right)^t} \tag{19}$$

$$Present\ worth\ of\ operating\ cost_{i,t} = \frac{operating\_cost_i * \left(1 + OCgrowth\_rate_i\right)^{t-1}}{\left(1+r\right)^t} \tag{20}$$

$$c_{i,t} = Present\ worth\ of\ operating\ cost_{i,t} + Present\ worth\ of\ \ fuel\ cost_{i,t} \tag{21}$$

$c_{i,t}$, as explained earlier, is the present worth of the total amount of variable cost for each generator *i* in year *t*. The values for the variable costs and growth rates from equation 19 – 20 are found in Appendix B.

4.2.4 Investment Cost

The cost of investing in new capacity, $inv_{t,s}$, in this example is assumed to be the present worth of capital cost measured in $/MW. Capital costs in this context are the one-time costs related to building the generators' facilities. The method of calculating the capital cost is done in a manner similar to the work done by Pirnia (2009) who assumes that the salvage value (the value of the facility at the end of its life) is zero. Furthermore, to calculate the depreciation of the assets' value, Prinia (2009) uses the straight line depreciation method where facilities depreciate by the same amount each year. The investment cost, $inv_{t,s}$, is therefore calculated as shown in equation 22.

$$inv_{t,s} = building\_cost_i * 1000 * \frac{\min\{22-t/age_i, 1\}}{(1+r)^t} \tag{22}$$

The first part of the equation (*building_cost$_i$*1000)* is simply the conversion from \$/KW to \$/MW. Because *building_cost$_i$*, the building cost of generator *i*, is in \$/KW while the rest of the model is in terms of MW, it is necessary to convert \$/KW to \$/MW by multiplying by 1000. This value is then multiplied by the fraction $\min\{22 - t/_{age_i}, 1\}$ to allocate the proportion of the cost which will be used within the model's time horizon (years *t, t+1, ... , 21*), i.e. to leave out the portion which, in the real world, would also be used in years 22 and later. Finally the result is divide by $(1+r)^t$ to obtain the present worth. Both the *building_cost$_i$* and the *age$_i$* parameters are found in Appendix B.

4.2.5 Existing Generation Capacity

At the start of the model, a realistic assumption is made stating that some generators already exist in the system. These existing generating capacities, after depreciation, are used in the model as parameter $exK_{i,t}$. This parameter, for each generator *i* during year *t*, is the value for the existing generation capacity, after depreciation, that has been built prior to the start of the model. The values chosen for this example are taken from the IPSP and are shown in Appendix B. Note how the phasing out of coal by 2014 is represented by dropping the capacity to zero at time period 9.

4.2.6 Maximum New Generation

One of the constraints in the model allows the modeller to enforce a physical limitation on the maximum amount of new capacity of a certain generation type that can be built. The parameter $maxcap_i$is used to specify what this maximum limit for each generation type i is. In this example, only one limitation is enforced related to how much of each hydro generation type (small, medium and large hydro generators) can be built. These values, in MW, are related to the physical availability of viable unused water sources that can be utilized to generate power. The data is obtained from the IPSP and the parameter values are found in Appendix B.

4.2.7 Maximum Ramp Up/Down Rate

Ramping constraints 7 – 8 depend on up_i and dn_i, the parameters in fraction per minute measuring the generators' maximum ramp up and down rates respectively. Unfortunately, ramping capabilities of individual generators (in MW/min) which are necessary to calculate the up_i and dn_i parameters are not publically available. For this reason, these values were determined based on approximations made by observing Ontario's current system generators and analyzing the most recent year's hourly output.

As of 2013, which is the most recent individual generator output data published online, Ontario had 89 generators of the different types. In order to determine the ramping capability of each generator type, the ramping capability of each available generator had to first be determined. This was done by observing the maximum increase and decrease in output between all consecutive hours throughout the entire year. Note that the data was first observed and cleaned up to exclude all hours before and after a generator was started up and shut down to eliminate exceptional behaviour. Once these values were estimated, data on each generator's capacity (in MW) was obtained and the ramping capabilities in MW/min were divided by the capacities in MW to obtain the ramp up and ramp down rates in fraction per minute. Next, all similar generators were grouped together, and each generator group's maximum and minimum of the calculated ramp up and ramp down rate was selected as the generator type's parameters up_i and dn_i. It is important to note however that the generator ramping capabilities found through data observation are conservative as the generators may actually have the ability to ramp up and down to a greater extent than was observed. Therefore, the estimates for the up_i and dn_i parameters found in Appendix B are also conservative in nature.

4.2.8 Maximum Rate of Change Upward/Downward of Demand

The rate of change of net demand (in MW/min) is basically the difference in net demand between two consecutive minutes. In order to determine the future net demand rate of change levels, and consecutively the maximum of those values, previous historic data was observed in hopes of finding a pattern or correlation between the change in the maximum rate of change from one year to the next as the level of wind penetration increased over the years. Unfortunately, because minute-to-minute data was unavailable, hourly data was used and the MW/hr rates found were then converted to MW/min by dividing by 60.

After observing the maximum rate of change, both upward and downward, of net demand from 2007 until 2014, it was clear that no real pattern exists. The level of net demand seemed to fluctuate slightly from year to year and did not follow a steadily increasing or decreasing pattern. The zigzagging of the maximum rate of change of net demand from year to year can be observed in figures 7 and 8. Furthermore, as shown in figure 9, the level of predicted wind output was expected to steadily increase over these years. This lack of obvious pattern and correlation, and because the values of the maximum rate of change upward and downward of net demand were relatively close from year to year, the parameters $rup_{t,s}$ and $rdn_{t,s}$ were estimated as the average of all historic maximum rates of change and was taken as a constant over the 21 year model time frame. The estimated values used in the model can be found in Appendix B.

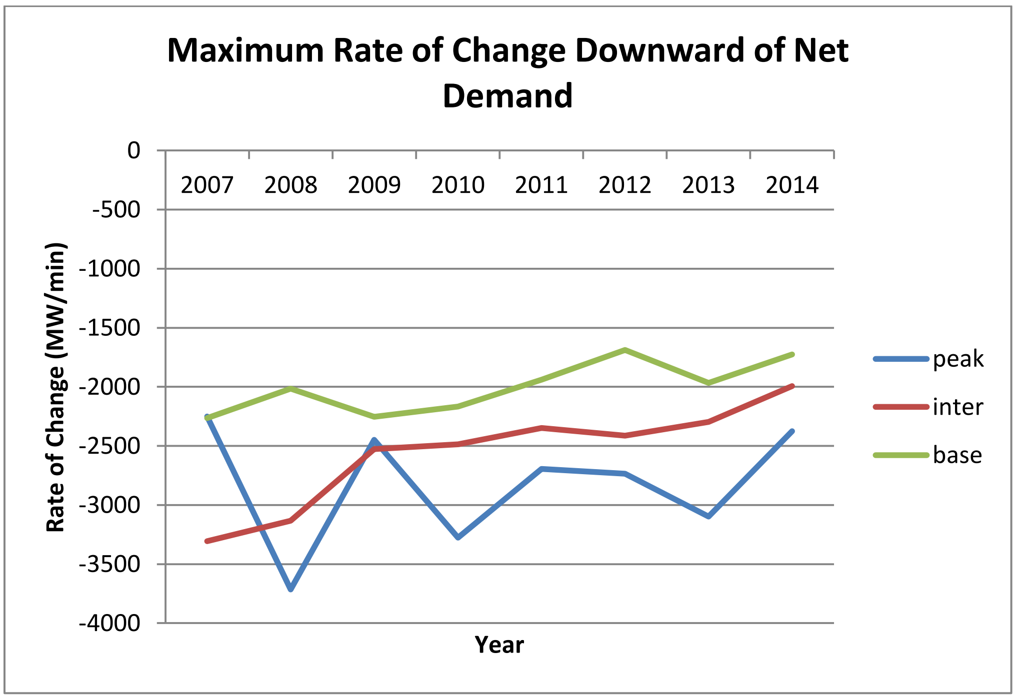

Figure 7 - Maximum Rate of Change Downward of Net Demand

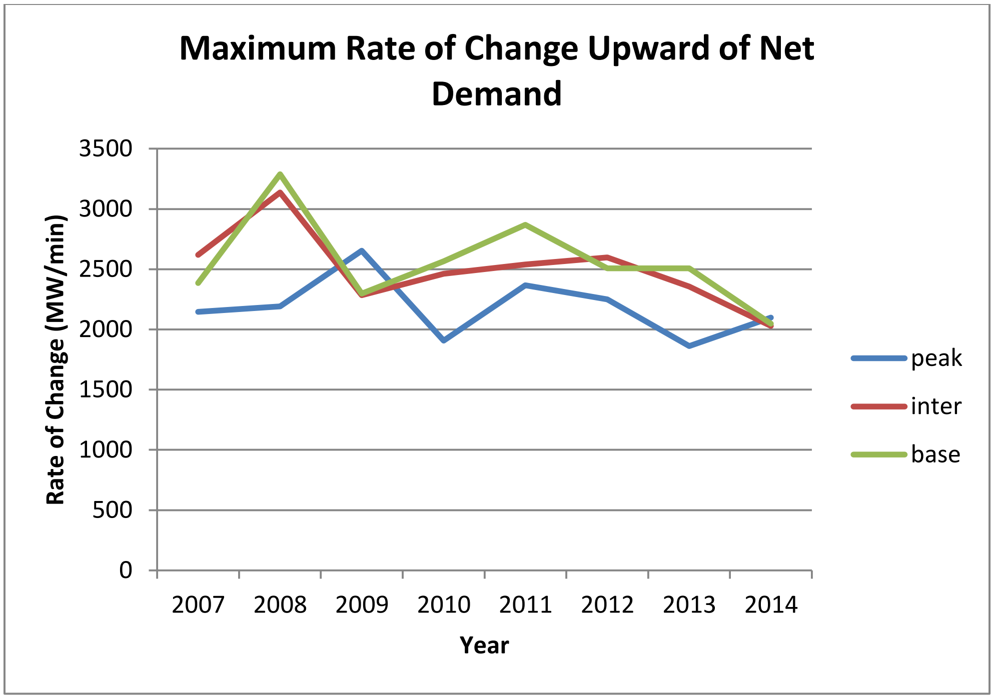

Figure 8 - Maximum Rate of Change Upward of Net Demand

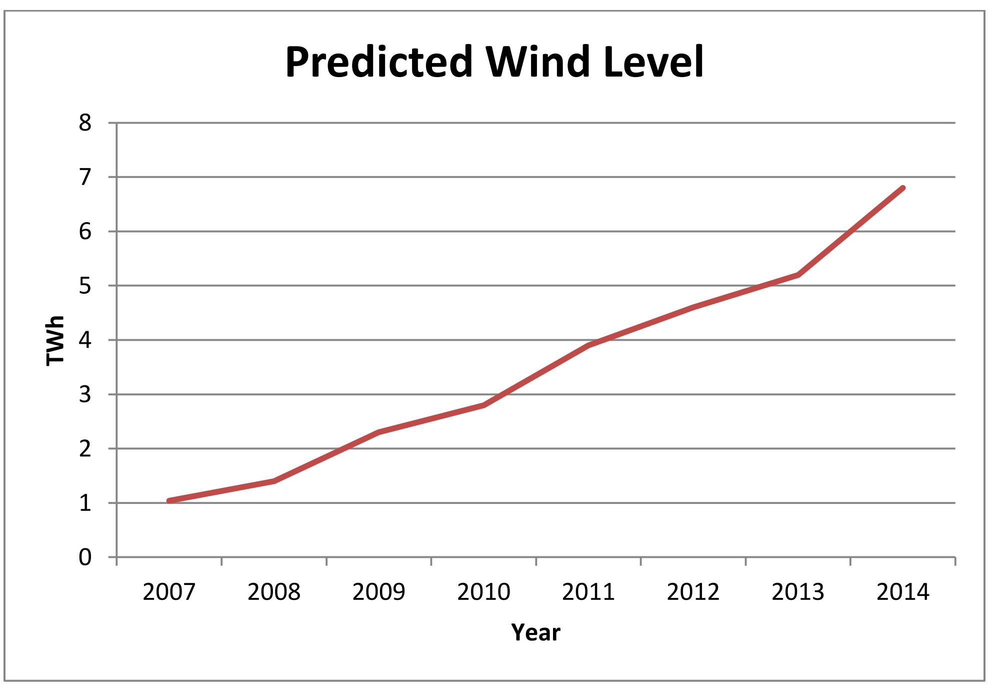

Figure 9 - Predicted Wind Level

4.2.9 Time for Generator to Ramp Up and Down from One Demand Block to the Next

Depending on the number of demand blocks and what a typical day's demand looks like, several parameters, detailing how many hours a generator has to move from one demand block to another, are needed. As mentioned earlier, the experiments done in this chapter are based on a scenario with 3 demand blocks: peak, intermediate and base. In order to pinpoint the parameters needed, we require a better picture of what a typical day's demand in Ontario looks like.

According to the Ontario Energy Board (OEB), the demand for electricity in Ontario is seasonal, where 2 seasons exist: summer and winter. The summer season is composed of approximately 184 days from the 1st of May to the end of October, while the winter season is composed to about 181 days from the 1st of November to the end of April. Furthermore, after observing hourly demand data for the years 2007 – 2013 obtained from the IESO, it was found that summer days have a single peak that occurs from noon to about 4:00 pm, while winter days have two peaks, the first occurring between 7:00 am and 10:00 am, and the second occurring around 6:00 pm. With this information in mind, and based on the province's smart meter pricing according to the time of use (Ontario Energy Board, 2015), the daily seasonal schedules found in figure 10 were composed. Note that green represents the hours in the base demand block, orange represents intermediate and red represents peak.

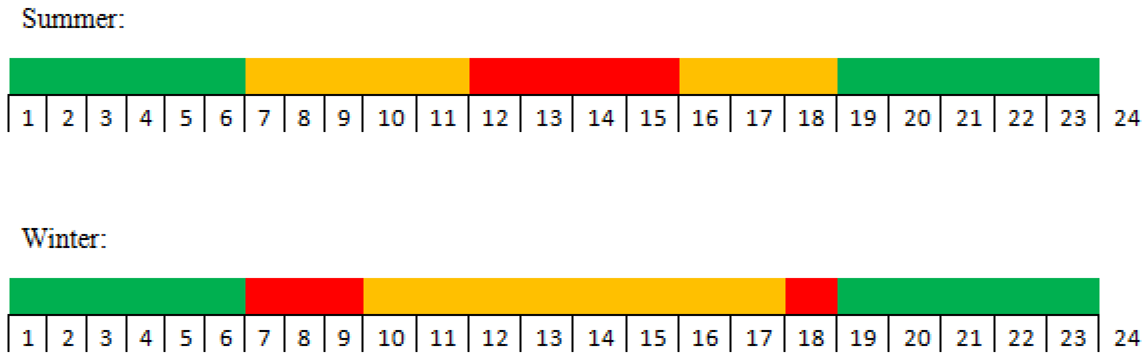

Figure 10 - Summer and Winter Schedules

Notice from the schedules obtained that in both the summer and winter seasons 12 hours of the day belong to the base demand block, 8 hours belong to the intermediate demand block, and 4 hours belong to the peak demand block. These values are consistent with the parameters discussed in chapter 4.2.2.

With both schedules in mind, it is observed that generators make the following transitions:

- Base to intermediate
- Intermediate to peak
- Peak to intermediate
- Intermediate to base
- Base to peak
- Peak to base

If we are following the logic described in chapter 3.2.2.1, then the generators have the following amount of hours to move from one demand block to another:

- *rBI* : Base to intermediate: 12 hours
- *rIP*: Intermediate to peak: 5 hours in the summer, 8 hours in the winter

- *rPI* : Peak to intermediate: 4 hours in the summer, 3 hours in the winter
- *rIB:* Intermediate to base: 3 hours
- *rBP:* Base to peak: 12 hours
- *rPB*: Peak to base: 1 hour

Notice that for ramping from intermediate to peak and peak to intermediate, there are 2 different times depending on the year. Because increasing the number of hours that a generator has to ramp up or down from one demand block or another relaxes the relevant constraints, the smaller of these values is considered. Note that, as the third experiment conducted demonstrates, the selection of the parameters used in the model is important for the behaviour of the model. The experiments done and the results obtained in this chapter only serve to demonstrate the methodology used and the followed process. Due to the approximations and assumptions made in obtaining the data for the experiment, the results are not accurate enough to serve as final results suitable for policy recommendations.

4.2.10 Maximum Wind Drops

Parameters bp_t, bi_t, and ip_t are used in the model to represent a sudden drop in wind that the system would then have to ramp up to meet. To approximate these value, transition hours between base and peak, base and intermediate, and intermediate and peak were observed for the year 2007 in Ontario. The maximum drop of wind that occurred during each of these 3 groups was then recorded to compose the 2007 values for bp_t, bi_t *and* ip_t. Next, from the forecasted data of how much wind is expected to be produced each year, the percentage increase of wind production between each year and the next was calculated. The values of bp_t, bi_t *and* ip_t were then increased by these percentages to estimate the values for years 2 – 21. For example, if wind production was expected to increase from 1.4 TWh in 2008 to 2.3 TWh in 2009 (64% increase), then the maximum wind ramps, bp_t, bi_t, and ip_t would also increase by 64% from 2008 to 2009. The obtained values are found in Appendix B.

4.3 Experiment Results

As stated earlier, the experiments conducted served two main purposes. The first purpose is to highlight that the new model that includes the new constraints discussed yields results that differ greatly from the traditional model sans constraints. The first experiment conducted revolves around attempting to highlight this point. It is worth reiterating however that although realistic data has been used from Ontario's generation mix, many parameters have been grossly estimated as shown throughout this report. It is for this reason that the results obtained here are not accurate measures and do not serve to provide a rigid plan to be followed by the Ontario planners. Instead, the experiments transparently demonstrate the approach and methods used and can be easily replicated using more precise parameters obtained after a more detailed analysis. The second purpose of the experiments - experiment 2 in particular - is to demonstrate the importance of conducting further analysis before the use of the model due to the sensitivity of the model to some of the parameters.

4.3.1 Experiment 1 Results

In the first experiment, the old model, without the ramping constraints, is run and the results are compared with the output obtained by running the new model that includes the ramping constraints discussed in section 3.2.

To obtain the optimal values of each generation type to be built over the years under the two different models, the model described in chapter 3 has been programmed in GAMS (General Algebraic Modeling System). The code for both the old and new model is found in Appendix C.

The old model, run over 21 years, is a linear program given by the formulation in chapter 3.1. The model calculates the amount of power generated from each generation type in each demand block over the years ($X_{i,t,s}$), the new capacity built of each generation type in each year ($I_{i,t}$), and the total capacity available of each generation type during each year ($K_{i,t}$). This makes for a relatively large optimization problem composed of 1,156 variables and 999 constraints. The new model that is also run over 21 years, is exactly the same as the old model with the addition of the constraints found in chapter 3.2. This new model also solves for how much each generator type needs to produce to make up for the sudden drops in wind simulated under worst case scenario conditions ($BP_{i,t}$, $BI_{i,t}$, $IP_{i,t}$). In addition to the variables and constraints seen in the old model, the new model has 703 more variables and 1,580 more constraints. In both cases the LP GAMS CPLEX solver is used and an optimal solution is obtained. In order to compare the results of both models solved, the outputs were processed and the graphs shown in figures 11 – 14 were constructed. Figures 11 and 12 are outputs of the old model while figures 13 and 14 are those of the new model.

Figures 11 and 12 are outputs of the old model and show the annual electricity production (in MW) for all existing and new generator capacities respectively. It is worth highlighting that because coal plants were expected to be completely shut down by the end of 2014 (year 8), no power is produced by the existing coal plants after that point. Furthermore, because of the expected shut down of existing nuclear facilities during the later years of the model, the production using existing nuclear facilities also drops as is evident from figure 11. Figure 12 on the other hand shows the annual electricity production (in MW) for the new generator capacities invested in from the start of the model period. Notice how as the years go by nuclear production increases and some gas production is introduced, while the other generation productions remain relatively consistent. Generation from new nuclear facilities seems to increase to replace the dropping generation from existing nuclear facilities.

One observation made here that influenced the design of the ramping and sequencing constraints introduced in the new model, is the behaviour of some of the generators. For example, when looking at the new generation type outputs in figure 12, it can clearly be observed that the hydro plants do not ramp up or down at all – their production remains constant throughout the years and from one demand block to another. Furthermore, gas generators are turned on during peak hours, which is consistent with what is observed in real world scenarios due to the high ramping capabilities of gas generators (their ability to quickly ramp up and down to meet changes in net demand). The issue however occurs with the nuclear generation. As shown in the figure, nuclear output varies largely from one demand block to another within a certain year. Looking at year 9 for example, the level of production during peak hours is at 5452 MW, while the level during intermediate and base hours is 1767 MW and 0 MW respectively. Similar results are observed throughout the rest of the years. The model therefore seems to suggest using nuclear generators as ramping generators which contradicts their usage as baseload generators in real life systems. When observing the Ontario power system and various power systems across Europe, for example, it is quite evident that nuclear is only used as a base load power generation source, meaning that it is used to meet minimum demand levels and is not ramped to a large degree as is suggested by the model.

In comparison, when the new model is run, the production levels of the new generation plants change to those shown in figures 14. Much lower variations in nuclear from one demand block to the next are observed which is consistent with real world observations. Furthermore, the new gas generation plants (simple gas cycle plants) are only used during peak hours and to a much larger degree than that observed in the old model. This is mainly due to their higher variable cost and their ability to ramp at faster rates than other generators. As for production levels of the old existing generators, we observe similar results that are less drastic (figures 11 and 13). There is no ramping of hydro generators, for example, in the old model output (as observed in figure 11), while the new model ramps the hydro sources slightly (figure 13).

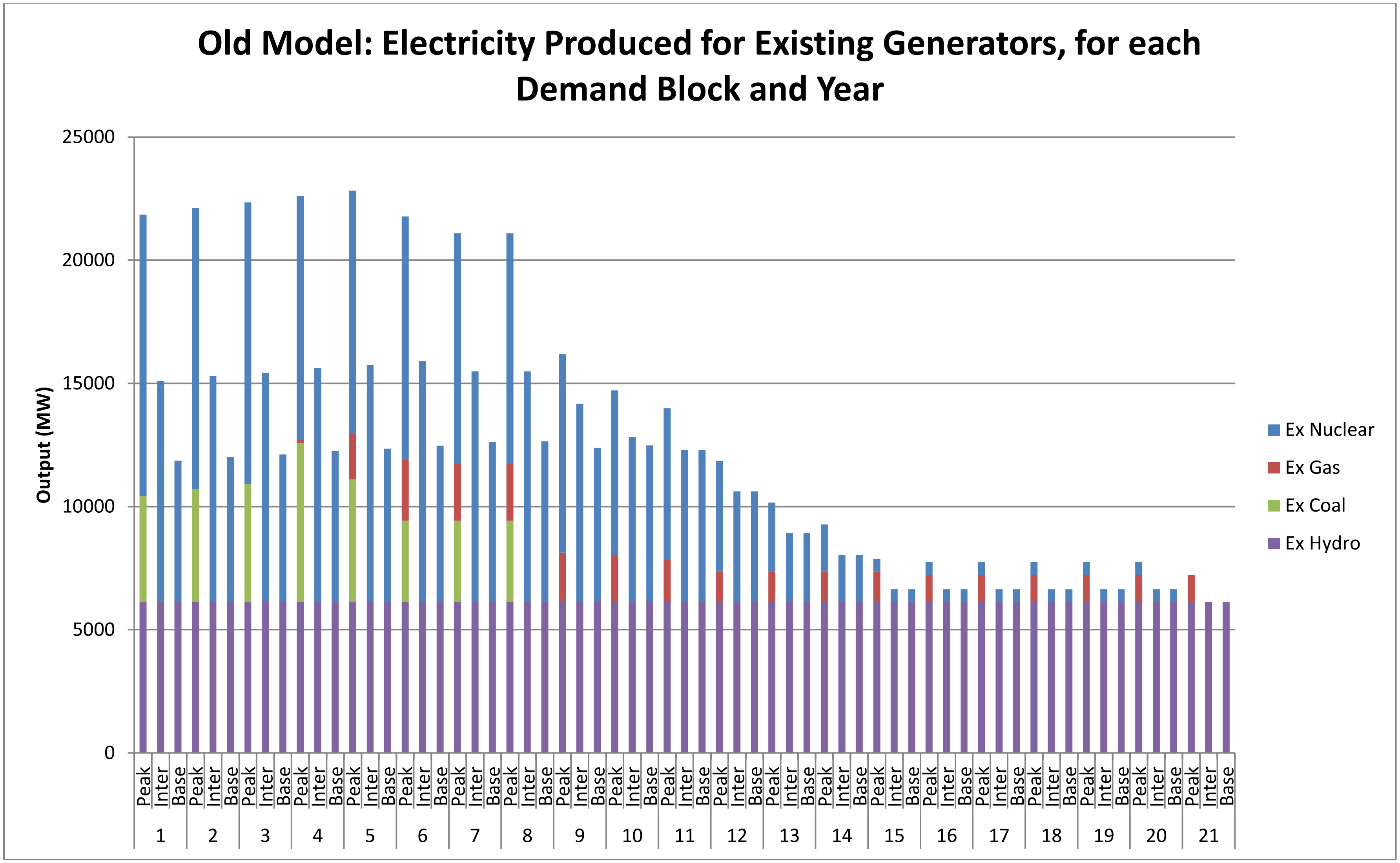

Figure 11 - Old Model: Electricity Produced for Existing Generators, for each Demand Block and Year

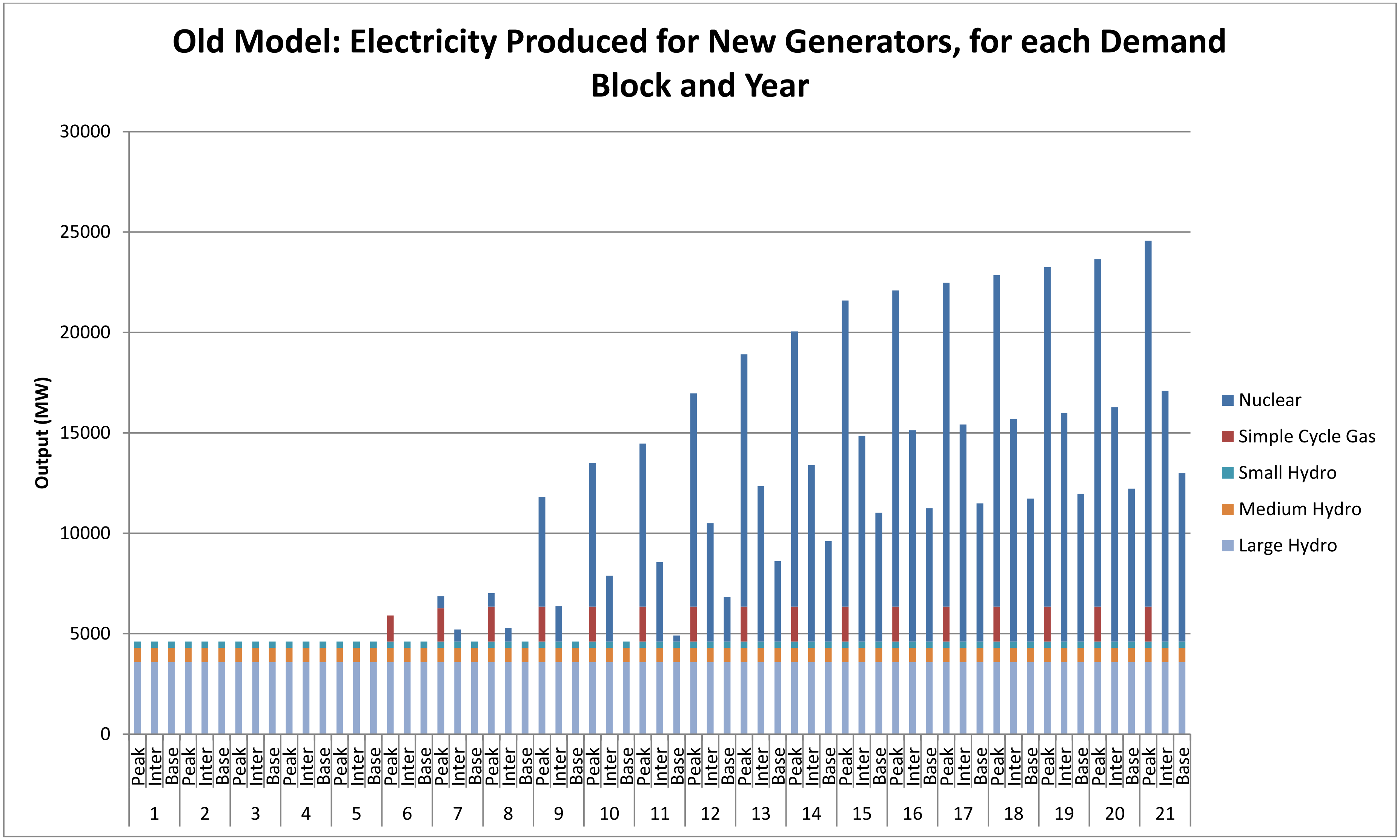

Figure 12 - Old Model: Electricity Produced for New Generators, for each Demand Block and Year

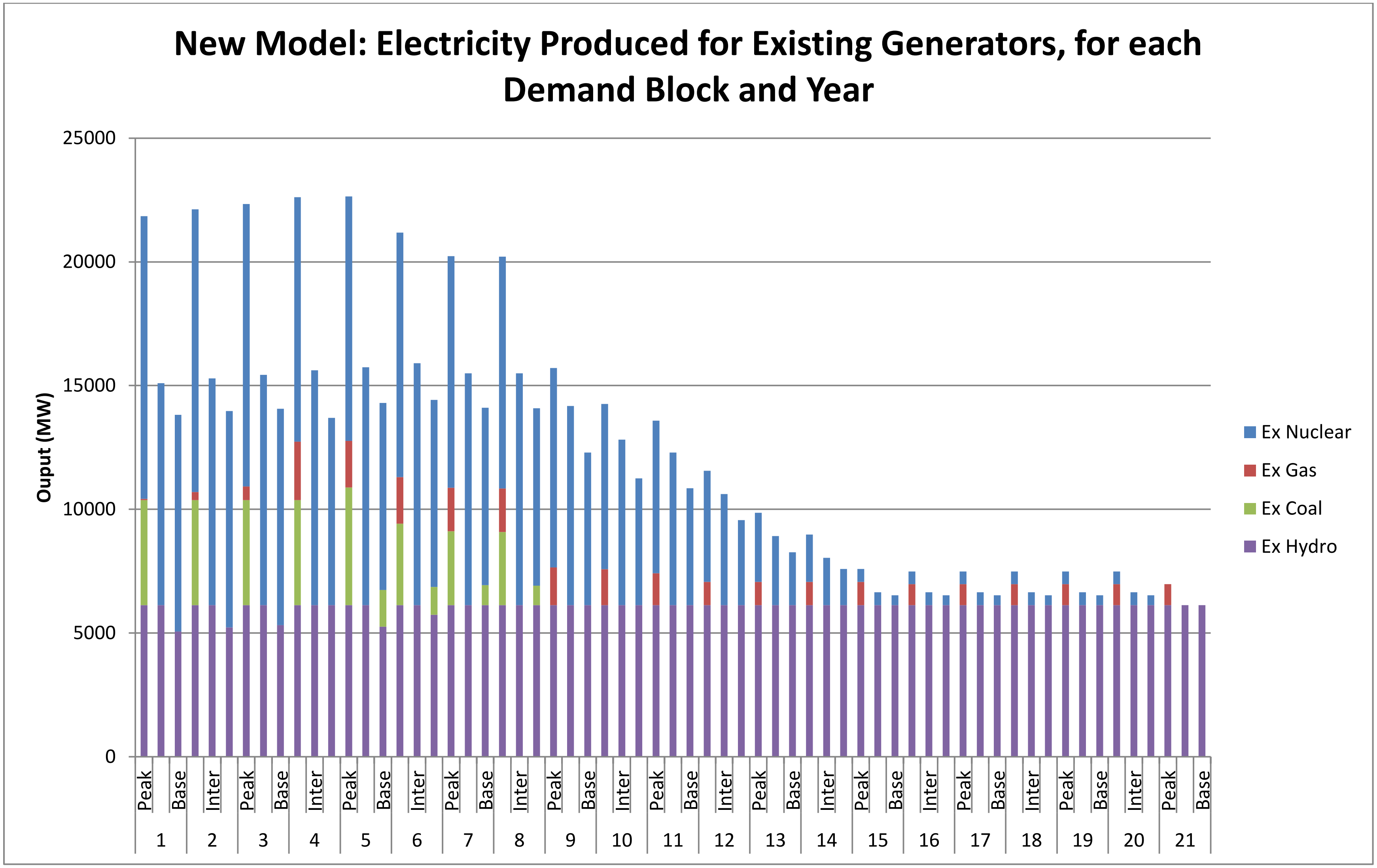

Figure 13 - New Model: Electricity Produced for Existing Generators, for each Demand Block and Year

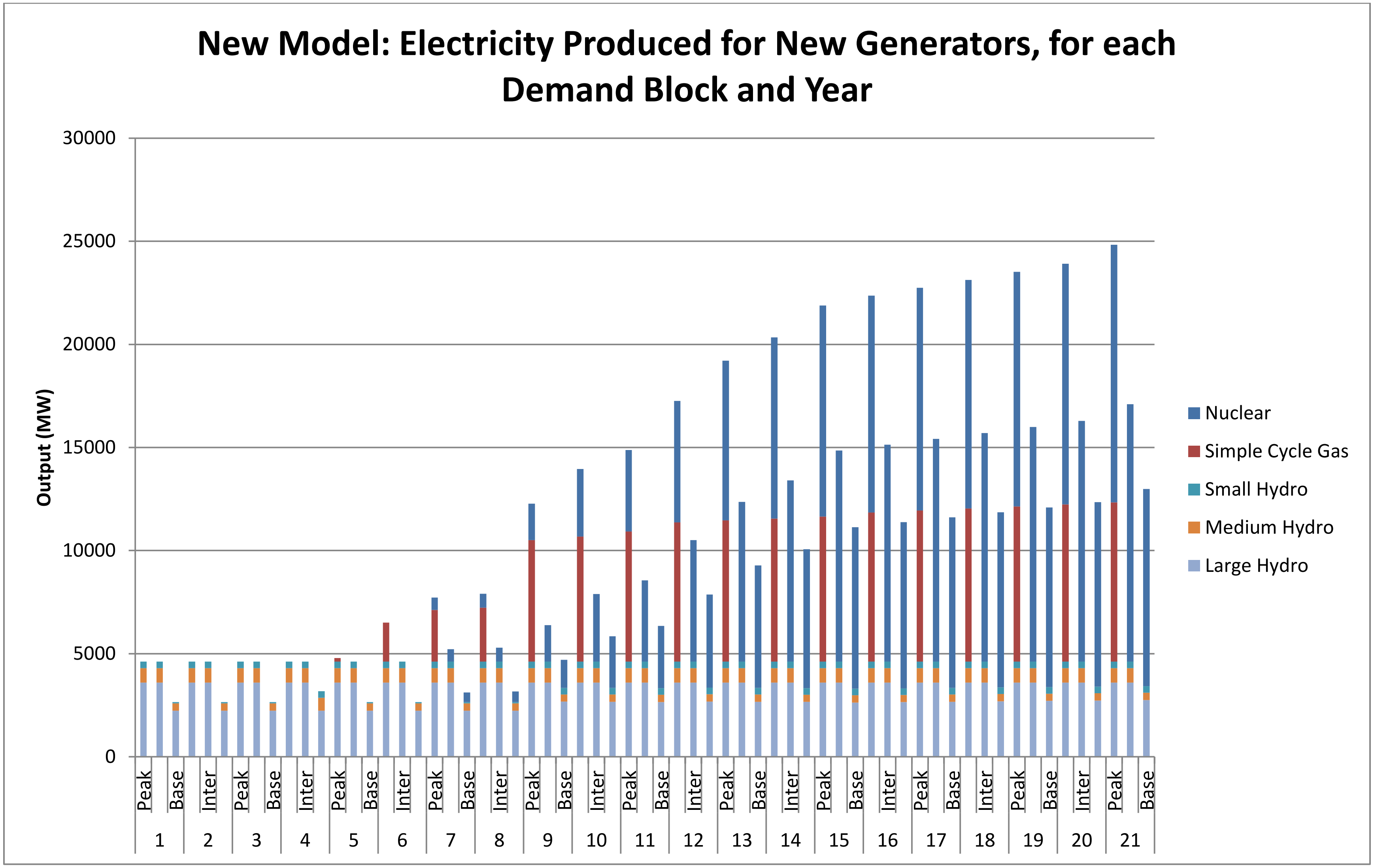

Figure 14 - New Model: Electricity Produced for New Generators, for each Demand Block and Year

In addition to power production, and more importantly, both models solve for the total capacity of each generation type in each year. This forms a recommendation on how much new capacity of each generation type is to be built each year over the model time horizon to meet the expected demand while considering physical and technical limitations. Because no new investments are allowed to be made in old existing generators, the total capacity of each old existing generation type remains the same for both the old and new model. Figure 15 shows the levels of the existing generation types as they depreciate year after year. Note that the values for these capacities are fed into the model as a parameter in this case.

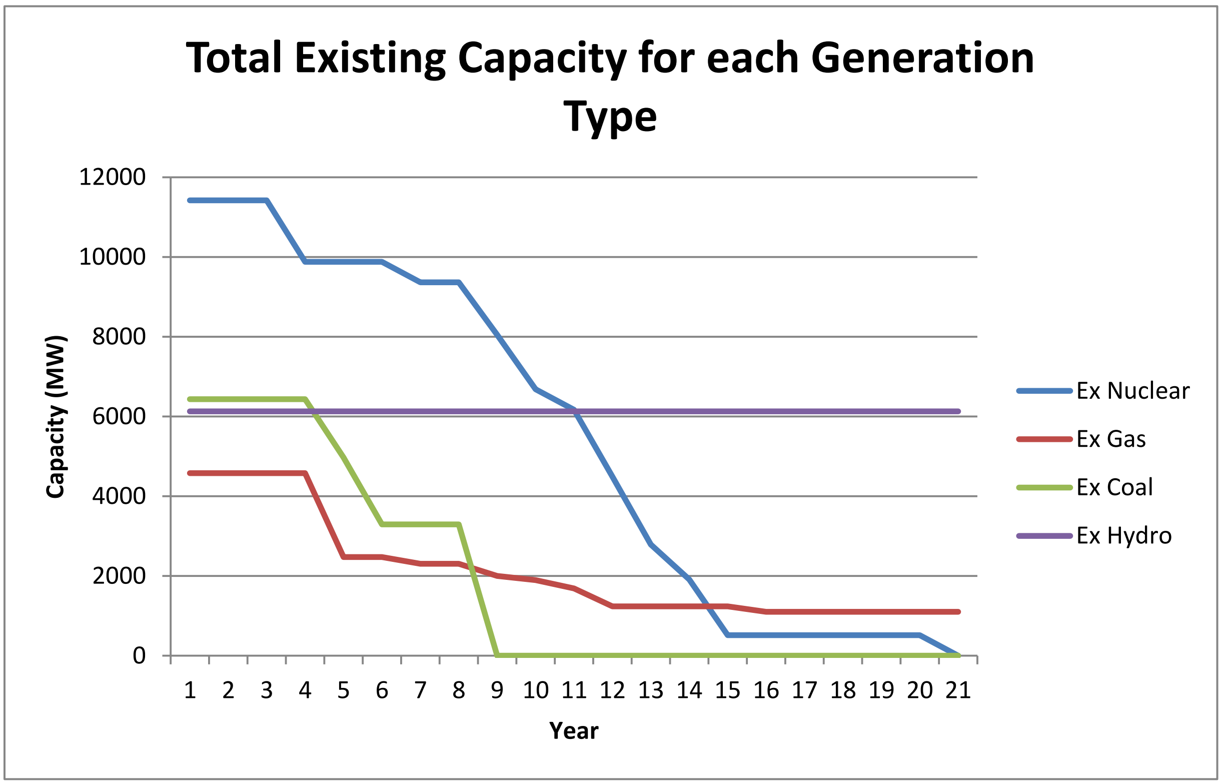

Figure 15 - Total Existing Capacity for each Generation Type

The capacity expansion model chooses what generation types to invest in based on their limitations (capacity in the old model and both ramping and capacity in the new model) and economic efficiency (cost of investment and production). Figures 16 and 17 show the total amount of capacity of new generation types each year after they have been built. Notice that in both the old and the new model, hydro facilities are built to their maximum physical limitation at the beginning of the planning period due to their relatively low costs, and therefore high economic efficiency. Furthermore, due to the present worth formulation in the model, these generation types are favoured to be built as early as possible. As for nuclear and gas generation types, a slow investment in both is observed starting in the 5th year. These new capacities are needed as soon as drops in the existing generator capacities are observed (figure 15). As existing capacities slowly shut down and decrease (figure 15), investments in new capacities are made and new generators are built (figures 16 and 17).

When comparing the new capacities built in the old model vs the new model, the significant difference between the amount of nuclear and gas generation constructed stands out. Overall, less nuclear capacity and more gas capacity is constructed in the new model compared to the old one. Once again, these results can be explained by the added consideration of whether or not generators individually have the ability to meet ramping restrictions. Because nuclear is found to be less capable of quickly ramping up and down while gas is found to be a better ramping generator, investments in both are made to reflect the need to have sufficient ramping capabilities.

One final observation to make here is to note that, in the new model, constraints 7 and 8 are not found to be binding with the current data set and can be removed from the model completely in this case. Under different conditions where a pattern is found between the increase in renewable penetration and the maximum ramping of net demand, these constraints are expected to take effect. Unfortunately, with the current data set such a correlation could not be made, and the parameters related to maximum and minimum ramping of net demand ($rup_{t,s}$ and $rdn_{t,s}$) were kept at a constant average value resulting in a relaxed constraint. Furthermore, with the current data, only sequencing constraints 9 and 13 were found to be binding. Constraint 9 deals with the ramping up from base to peak, while constraint 13 deals with ramping down from peak to base. Both movements involve a relatively larger change from one generation level to another compared to, for example, ramping from base to intermediate to intermediate to peak etc.

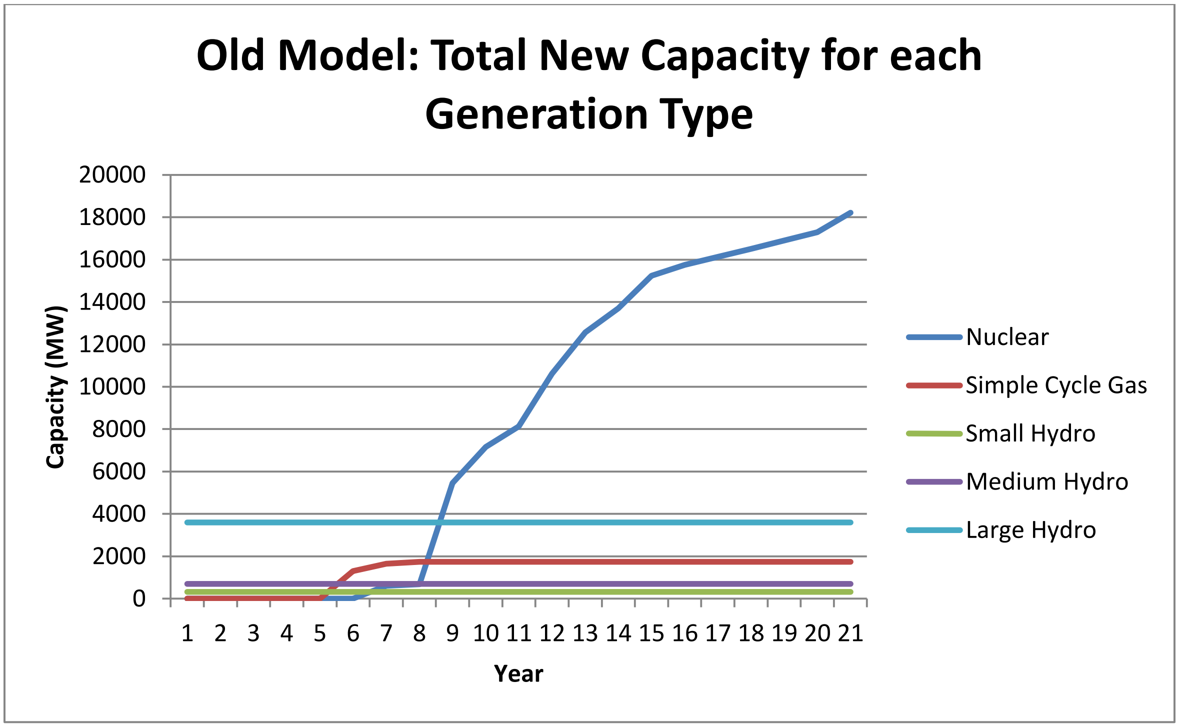

Figure 16 - Old Model: Total New Capacity for each Generation Type

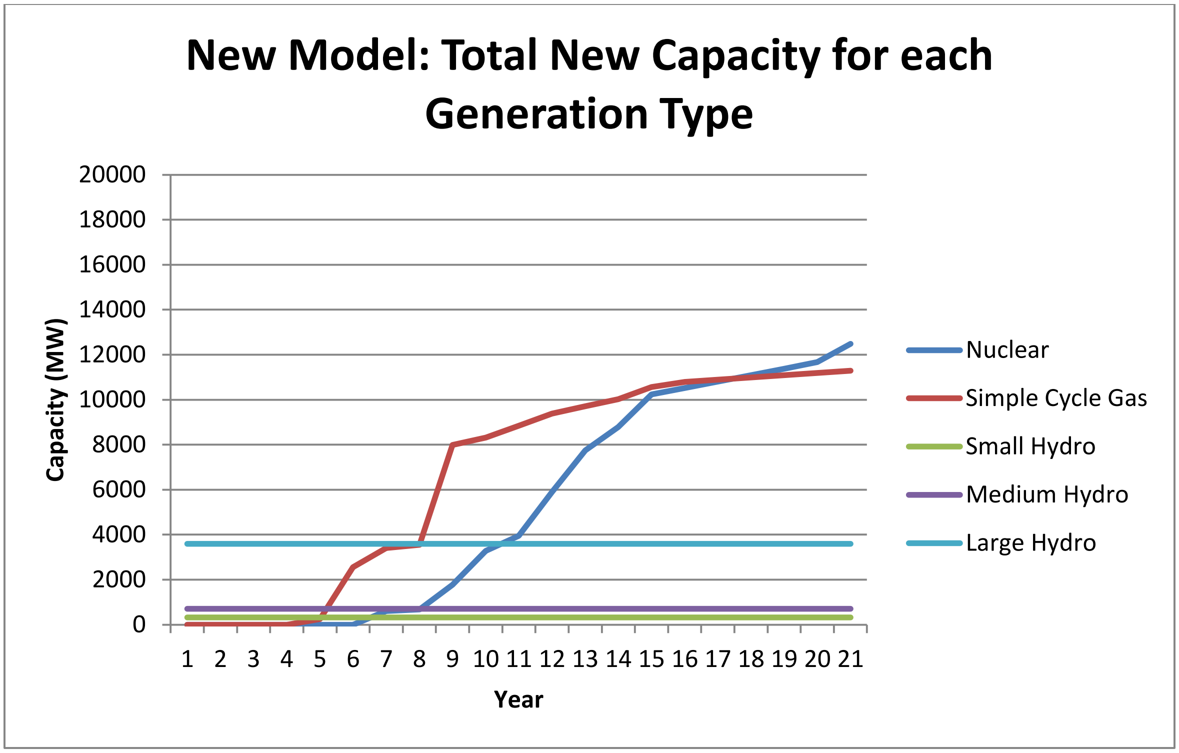

Figure 17 - New Model: Total New Capacity for each Generation Type

4.3.3 Experiment 2 Results

To further emphasize that the results obtained in this chapter are not meant to be used as final implementation plans, and to demonstrate the sensitivity of the new model to some of the parameters used and therefore to highlight the importance of their selection, a final experiment was conducted where the new parameters introduced in our new model were changed. The focus of this experiment is to show that the suggested amount of investment in different generation capacities heavily depends on how their individual ramping capability is defined. Because the constraints dictating how much a particular generator type can ramp up and down depend on the modeller's choice of how many hours the generators have to move from one demand block to another (*rBI*, *rIP*, *rPI*, *rIB*, *rBP*, *rPB*), changing those parameters and observing the effect will be the focus here.

In the previous experiments, the parameters (*rBI, rIP, rPI, rIB, rBP, rPB*) used were as they were defined in chapter 4.2.9. These values have been adjusted as follows:

- *rBI* : Base to intermediate: reduced from 12 hours to 8.5 hours
- *rIP*: Intermediate to peak: reduced from 5 hours to 4 hours
- *rPI* : Peak to intermediate: constant at 3 hours
- *rIB:* Intermediate to base: increased from 3 hours to 7.5 hours
- *rBP:* Base to peak: reduced from 12 hours to 7.5 hours
- *rPB*: Peak to base: increased from 1 hour to 6.5 hours

Recall that the values for these parameters were previously obtained by observing how many hours a particular generator theoretically had to move from one demand block to another in the schedules found in figure 10. For this experiment however, instead of calculating the parameters this way, the midpoint from one demand block to the midpoint of the adjacent demand block is considered instead. For example, consider the movement from base to peak in the figure 10 schedule. Previously, we allowed the generator the full 12 hours available during the base demand block to adjust its ramping and transition to the peak demand block. In this experiment however, the midpoint to midpoint is taken instead of the starting point (hour 19) to the end point (hour 6), therefore 6 hours from base (half of 12) and 1.5 hours from peak (half of 3) are added to obtain a totally of 7.5 hours to transition from the base to peak demand block. Note that these are all approximations and the values are based on averages.

After this change was made, the model was once again run in GAMS. The focus here is how the capacities invested in over the years have changed. For the three different hydro generation types, the amount invested in was found to be the same. Once again, because hydro is the most economical source and has relatively good ramping abilities, it makes sense that the model would attempt to maximize its investment in that generation type before moving on to other types. The differences in investment occurred in how much nuclear and gas was built as shown in figures 18 and 19. Notice that although the investment in nuclear is less than in the original old model (without any of the constraints) it is still significantly higher than the new model with the original parameter values. Furthermore, the opposite is true in the case of investment in gas generation: although more gas generation capacity is built compared to the old model, significantly less is built than the new model with the original parameter values.

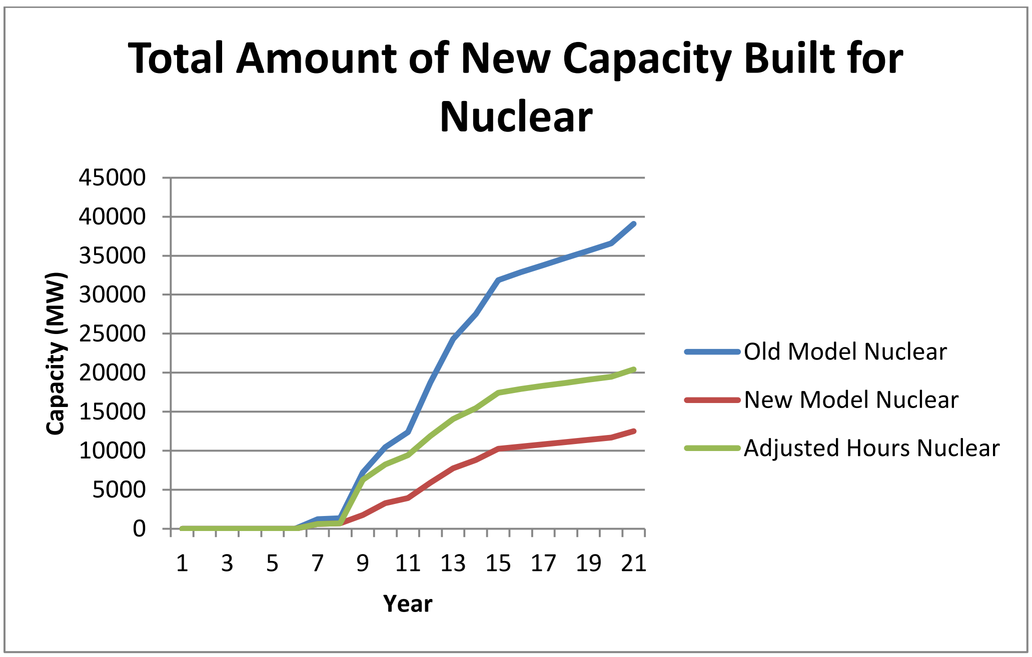

Figure 18 - Total Amount of New Capacity Built for Nuclear

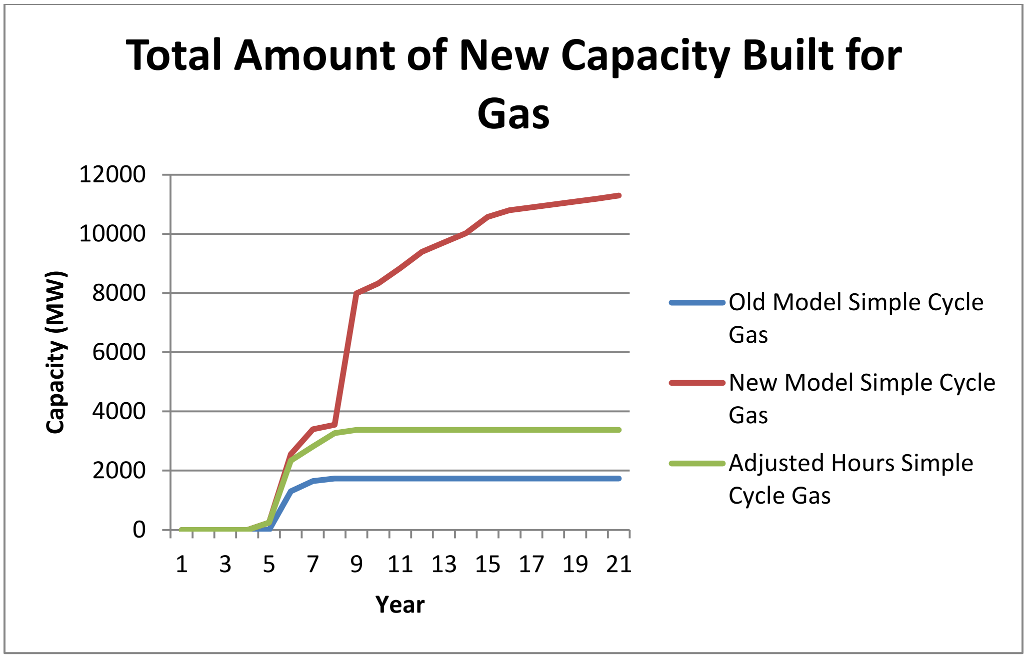

Figure 19 - Total Amount of New Capacity Built for Gas

To understand why these differences in investment amounts occur, it is necessary to consider how the parameters constrain or relax the relevant constraints. Increasing the number of hours (*rBP, rBI, rIP, rPI, rPB, rIB*) results in a more relaxed constraint as the generators have more time to shift from one generation level to another. Reducing the number of hours however has the opposite effect and will force the generators to need to ramp at a faster rate. Recall that the values for *rBI, rIP* and *rBP* were reduced, while *rPI* was kept constant and *rIB* and *rPB* were increased. If all 6 constraints (equations 9 – 14) were binding constraints (therefore directly affecting the final solution) then because there seems to be more reduction than an increase in transitioning hours overall, one would expect the system to attempt to invest in faster ramping generation (more gas) as it is now further restricted and needs to ramp from one level to another at a faster rate. This however is not the case here. After the parameters were modified it was observed that constraint 13 was no longer binding in the model. Constraint 13 dictates the number of hours generators have to ramp down from peak to base (changed from 1 hour to 6.5

hours). This implies that the relaxation of *rPB* (the number of hours available to move from peak to base) from 1 hour to 6.5 hours relaxed the ramping constraint enough to make it ineffective thereby relaxing the results and allowing higher investment in cheaper nuclear generation and lower investment in more expensive gas generation as shown in figures 18 and 19. As observed, the change in how the parameters *rBP*, *rBI*, *rIP*, *rPI*, *rP* and *rIB* are defined changes the investment plan significantly. This therefore emphasizes the importance of spending more time in future works attempting to find more accurate methods of estimating these parameters.

5 Summary and Directions for Future Research

With the increased penetration of renewable energy sources into the power systems, it becomes important to account for their production when making long term investment plans to meet future electricity needs. This dissertation presents evidence that shows that accounting for renewable energy production and ensuring the system will be capable of ramping fast enough to meet varying demand yields vastly different investment plans than a simpler model that doesn't account for such operational details. This is especially true when it comes to the amount of investment in generators designed for baseload and peak periods of the year.

Although this work runs some experiments using real data sources to highlight the differences in results between a model designed to account for ramping and a traditional model that does not, the results should not be used as final investment plans. Instead the steps taken in this work should be used as a framework for system planners to use with better parameter approximations, or future works that attempt to provide better methods of estimating the parameters necessary for the usefulness of the model, in practice.

Another direction for future research is as follows. In addition to the ramping short term constraints inspired from the unit commitment model, other short term constraints, such as generator start up and shut down decisions, may also hold some value in their inclusion. In their work, Wogrin et al. (2014) present an optimal thermal scheduling model using a newly proposed system state method that allows the inclusion of start up and shut down constraints. Including start up and shut down constraints may yield better results due to the inclusion of their costs. The use of the load duration curve simplifies the cost to being only dependent on the load level when in reality there are start up and shut down costs that are not accounted for when ignoring the relevant constraints.

References

AESO. (2008). Future Demand and Energy Outlook. Available at: http://www.aeso.ca/downloads/AESO_Future_Demand_and_Energy_Outlook.pdf

Blasing, T.J. (February 2014). *Recent Greenhouse GasConcentrations.* Available at: http://cdiac.ornl.gov/pns/current_ghg.html

Caramanis, M. C., Tabors, R. D., Nochur, K. S., & Schweppe, F. C. (1982). The Introduction of NonDIispatchable Technologies a Decision Variables in Long-Term Generation Expansion Models. *Power Apparatus and Systems, IEEE Transactions on*, (8), 2658-2667.

Department of Natural Resources. (2012). Electricity Demand Forecast: Do We Need the Power. Available at: http://www.powerinourhands.ca/pdf/Electricity-Demand-Forecast-Do-We-Need-the-Power.pdf

DOE (U.S. Department of Energy). (2008). *20% Wind Energy by 2030: Increasing Wind Energy's Contribution to U.S. Electricity Supply; Executive Summary (Revised).* NREL/TP-500- 42864; DOE/GO-102008-2578. *Golden, CO: National Renewable Energy Laboratory*

Government of Ontario. (2013). Achieving Balance: Ontario's Long Term Energy Plan. Available at: http://www.energy.gov.on.ca/en/files/2014/10/LTEP_2013_English_WEB.pdf

IEA (International Energy Agency). (2015). Renewable Energy. Retrieved July 23, 2015, from http://www.iea.org/aboutus/faqs/renewableenergy/

IESO. (2006). Integrating Wind Power: IESO Perspective on the Ontario Electricity System. *Independent Electricity System Operator.* Available at: http://www.ieso.ca/Documents/marketReports/WP_20061025-CanWEA-WindIntegration.pdf

IESO. (2015). Data Directory. Available at: http://www.ieso.ca/Pages/Power-Data/Data-Directory.aspx *GE Energy (2010). Western Wind and Solar Integration Study. NREL/SR-550-47434.* Golden, CO: National Renewable Energy Laboratory

Kirby, B. and M. Milligan (2005). *A Method and Case Study for Estimating the Ramping Capability of a Control Area or Balancing Authority and Implications for Moderate or High Wind Penetration.* Golden, CO, National Renewable Energy Laboratory. NREL/CP-500-38153.

Murphy, F. H., & Smeers, Y. (2005). Generation capacity expansion in imperfectly competitive restructured electricity markets. *Operations research,53*(4), 646-661.

Nicolosi, M. (2012). *The economics of renewable electricity market integration. An empirical and model-based analysis of regulatory frameworks and their impacts on the power market* (Doctoral dissertation, Universität zu Köln).

Ontario Energy Board. (2015). Power Smarter. Available at: http://ontarioenergyboard.ca/oeb/_documents/for%20consumers/tou_prices_winter.pdf

OPA. (2007). Integrated Power System Plan I. *Independent Electricity System Operator*. Available at: http://www.powerauthority.on.ca/integrated-power-system-plan/d-conservation-and-supply-resources

OPA. (2014). Generation and Conservation Tabulations and Supply/Demand Balance. 2013 LTEP: Module 3. Available at: http://powerauthority.on.ca/sites/default/files/planning/LTEP-2013-Module-3-Supply-Demand-Balance.pdf

Palmintier, B., & Webster, M. (2011). Impact of unit commitment constraints on generation expansion planning with renewables. *In Power and Energy Society General Meeting, 2011 IEEE* (pp. 1-7). IEEE.

Pirnia, M. (2009). Capacity Pricing in Electric Generation Expansion. MASc Thesis, Department of Management Sciences, University of Waterloo.

Sherali, H. D. (1982). Linear programming based analysis of marginal cost pricing in electric utility capacity expansion. *European Journal of Operational Research, 349-360.*

Short, W., Ferguson, T., & Leifman, M. (2007). *Modeling of Uncertainties in Major Drivers in US Electricity Markets* (pp. 17-22). NREL.

Tuohy, A., Meibom, P., Denny, E., O'Malley, M. (2009). Unit Commitment for Systems With Significant Wind Penetration. *Power Systems, IEEE Transactions on, vol.24, no.2, pp.592-601*.

United States Environmental Protection Agency. (2011). *Global Greenhouse Gas Emissions.* Available at: http://www.epa.gov/climatechange/ghgemissions/global.html

U.S. Energy Information Administration. (2014). *International Energy Statistics – Consumption.* Available at: http://www.eia.gov/cfapps/ipdbproject/iedindex3.cfm?tid=1&pid=1&aid=2&cid=ww,&syid=2008&eyid=2012&unit=QBTU

Van Beeck, N. (1999). *Classification of energy models*. Tilburg University, Faculty of Economics and Business Administration.

Wogrin, S., Duenas, P., Delgadillo, A., & Reneses, J. (2014). A new approach to model load levels in electric power systems with high renewable penetration. *Power Systems, IEEE Transactions on*, *29*(5), 2210-2218.

World Energy Council. (2013). *World Energy Resources 2013 Survey.* Available at: http://www.worldenergy.org/wp-content/uploads/2013/09/Complete_WER_2013_Survey.pdf

Appendix A

Indices:	
i	Power generation types
t	Time period in years
s	Demand blocks (ex: peak, intermediate, baseload)
Parameters:	
$d_{t,s}$	Net demand forecast (MWh)
h_s	Hours of year for demand block s
$c_{i,t}$	Present worth of total amount of variable cost (fuel cost and operating) for each generator type i in each time period in $/MWh
$inv_{t,s}$	Present worth of investment amount in new capacity type i in year t ($/MW)
$exK_{i,t}$	Existing generation capacities at start of model (MW)
$maxcap_i$	Maximum new capacity of each generation type (MW)
age_i	Age of generators over their entire life (years)
up_i	Maximum ramp up rate (fraction per minute)
dn_i	Maximum ramp down rate (fraction per minute)
$rup_{t,s}$	Maximum rate of change upward of demand in year t, block s (MW/min
$rdn_{t,s}$	Maximum rate of change downward of demand in year t, block s (MW/min)
rBP	Number of hours a generator has to ramp up from base level to peak level (hours)
rBI	Number of hours a generator has to ramp up from base level to intermediate level (hours)
rIP	Number of hours a generator has to ramp up from intermediate level to peak level (hours)
rPI	Number of hours a generator has to ramp down from peak level to intermediate level (hours)
rPB	Number of hours a generator has to ramp down from peak level to base level (hours)
rIB	Number of hours a generator has to ramp down from intermediate level to base level (hours)
bp_t	Maximum wind ramp from base to peak increased in proportion to predicted annual wind output (MW)
bi_t	Maximum wind ramp from base to intermediate increased in proportion to predicted annual wind output (MW)
ip_t	Maximum wind ramp from intermed to peak increased in proportion to predicted annual wind output (MW)

Variables:	
$X_{i,t,s}$	Power output level of type i generation in year t during demand block s (MW)
$I_{i,t}$	New added capacity of type i during year t (MW)
$K_{i,t}$	Total capacity of type i during year t (MW)
$BP_{i,t}$	Level produced by each generator i during t to make up from change in wind from base to peak
$BI_{i,t}$	Level produced by each generator i during t to make up from change in wind from base to intermediate
$IP_{i,t}$	Level produced by each generator i during t to make up from change in wind from intermediate to peak (MW)

Appendix B

Generator Type	up_i (fraction per minute)	dn_i (fraction per minute)
Nuclear	0.002	-0.0039
Coal	0.0093	-0.011
Simple Cycle Gas Turbine	0.0119	-0.0123
Combined Cycle Gas Turbine	0.0081	-0.0114
BioFuel	0.014	-0.012
Small Hydro	0.012	-0.0131
Medium Hydro	0.0102	-0.0083
Large Hydro	0.006	-0.0063

Table 2 - Maximum Ramp Up/Down Rate

Net Demand (MWh)		
Peak	**Intermediate**	**Base**
38630059	57551490	72131655
39031938	58118745	72812191
39354193	58523914	73247553
39751624	59076561	73902064
40058896	59445985	74279646
40420972	59922076	74815111
40818048	60465189	75448964
41053218	60681478	75590412
40855988	60029919	74427892
41201593	60460945	74887027
41553346	60901143	75357671
42077986	61683957	76339963
42442255	62142831	76834043
42812896	62611212	77340052
43023317	62755880	77358132
43573597	63576950	78388430
44130480	64407873	79431091
44694046	65248768	80486264
45264374	66099753	81554099
45841547	66960950	82634748
46425645	67832481	83728365

Table 3 - Net Demand d(t,s) in MWh

Fuel Cost Growth Rate	
Nuclear	0.02
Coal	0.01
Simple Cycle Gas Turbine	0.05
Combined Cycle Gas Turbine	0.03
BioFuel	0.03
Small Hydro	0
Medium Hydro	0
Large Hydro	0

Table 4 - Fuel Cost Growth Rate (Source: Pirnia, 2009)

Fuel Cost ($/MWh)	
Nuclear	6
Coal	27
Simple Cycle Gas Turbine	56
Combined Cycle Gas Turbine	56
BioFuel	23
Small Hydro	0
Medium Hydro	0
Large Hydro	0

Table 5 - Fuel Cost (Source: Pirnia, 2009)

Operating Cost Growth Rate	
Nuclear	0.03
Coal	0.01
Simple Cycle Gas Turbine	0.05
Combined Cycle Gas Turbine	0.05
BioFuel	0.03
Small Hydro	0.015
Medium Hydro	0.015
Large Hydro	0.015

Table 6 - Operating Cost Growth Rate (Source: Pirnia, 2009)

Operating Cost ($/MWh)	
Nuclear	1.5
Coal	0.5
Simple Cycle Gas Turbine	3.5
Combined Cycle Gas Turbine	2.75
BioFuel	4
Small Hydro	1
Medium Hydro	1.5
Large Hydro	1.5

Table 7 - Operating Cost (Source: Pirnia, 2009)

Building Cost ($/KW)	
Nuclear	50,000
Coal	50,000
Simple Cycle Gas Turbine	665
Combined Cycle Gas Turbine	1174
BioFuel	2096
Small Hydro	3700
Medium Hydro	2750
Large Hydro	2000

Table 8 - Building Cost (Source: Pirnia, 2009)

Generator Life	
Nuclear	30
Coal	10
Simple Cycle Gas Turbine	20
Combined Cycle Gas Turbine	20
BioFuel	20
Small Hydro	75
Medium Hydro	80
Large Hydro	100

Table 9 - Generator Life (Source: Pirnia, 2009)

Existing Generating Capacities (MW)																					
Year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
Nuclear	11419	11419	11419	9879	9879	9879	9363	9363	8050	6686	6170	4487	2792	1911	515	515	515	515	515	515	0
Coal	6434	6434	6434	6434	4969	3293	3293	3293	0	0	0	0	0	0	0	0	0	0	0	0	0
Gas	4578	4578	4578	4578	2473	2473	2308	2308	2004	1897	1691	1236	1236	1236	1236	1105	1105	1105	1105	1105	1105
Hydro	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	6129	

Table 10 - Existing Generating Capacities (Source: Pirnia, 2009)

Maximum Capacity of New Generators (MW)	
Small Hydro	318
Medium Hydro	703
Large Hydro	3591

Table 11 - Maximum Capacity of New Generation (Source: OPA, Integrated Power System Plan - Exhibit D, Tab 5, Schedule 1, 2007)

Generator Type	up_i (fraction per minute)	dn_i (fraction per minute)
Nuclear	0.002	-0.0039
Coal	0.0093	-0.011
Simple Cycle Gas Turbine	0.0119	-0.0123
Combined Cycle Gas Turbine	0.0081	-0.0114
BioFuel	0.014	-0.012
Small Hydro	0.012	-0.0131
Medium Hydro	0.0102	-0.0083
Large Hydro	0.006	-0.0063

Table 12 - Maximum Ramp Up/Dn Rate

	Peak		Intermediate		Base	
Year	Min (MW/min)	Max (MW/min)	Min (MW/min)	Max (MW/min)	Min (MW/min)	Max (MW/min)
2007-2027	-45.96	34.97	-38.61	39.52	-30.76	40.09

Table 13 - Maximum Rate of Change of Net Demand

Year	bp_t (MW)	bi_t (MW)	ip_t (MW)
2007	94.00	85.00	56.00
2008	128.48	116.18	76.54
2009	209.05	189.03	124.54
2010	252.02	227.89	150.14
2011	346.84	313.63	206.63
2012	415.16	375.41	247.33
2013	467.72	422.93	278.64
2014	611.04	552.53	364.02
2015	991.44	896.52	590.65
2016	1081.57	978.02	644.34
2017	1171.70	1059.52	698.04
2018	1171.70	1059.52	698.04
2019	1261.83	1141.02	751.73
2020	1351.96	1222.52	805.43
2021	1532.23	1385.52	912.82
2022	1532.23	1385.52	912.82
2023	1532.23	1385.52	912.82
2024	1532.23	1385.52	912.82
2025	1532.23	1385.52	912.82
2026	1532.23	1385.52	912.82
2027	1532.23	1385.52	912.82

Table 14 - Maximum Wind Drops

Appendix C – GAMS Code

```
*All data based on that obtained from IESO, the IPSP and the LTEP
*Cost formulas based on the work done by M.Pirnia.

*==========================================================================
================================
* 1. Declare sets.

Sets
* Declare basic primary sets

 i                'Generation type'
                 /ExNuc,
                  ExGas,
                  ExCoal,
                  ExHydro,
                  Nuc,
                  SCGas,
                  CCGas,
                  Bio,
                  SHydro,
                  MHydro,
                  LHydro/

 t                'Time periods (annual)'
                  /T1*T21/
 s                'Demand block from clusted load duration curve'
                  /Peak, Intermediate, Base/
alias(t,tt)
;

*==========================================================================
================================
* 2. Declare parameters.

*Data from LTEP. Net Demand calculated by subtracting predicted wind output from
predicted total demand
Table p_D(t,s) 'Net Demand forecast (MWh)'
       Peak          Intermediate      Base
T1     38630058.83      57551490.07      72131655.1
T2     39031938.23      58118745.32      72812191.02
T3     39354193.38      58523914.05      73247553
T4     39751623.84      59076561.31      73902064.06
T5     40058895.81      59445985        74279646.27
```

```
T6      40420972.12       59922075.94       74815110.7
T7      40818047.93       60465189.15       75448964.47
T8      41053217.74       60681477.9       75590411.76
T9      40855988.23       60029919.38       74427892.33
T10      41201593.43       60460945.08       74887027.04
T11      41553345.88       60901143.09       75357671.37
T12      42077986.03       61683956.81       76339963.42
T13      42442255.2       62142830.95       76834042.98
T14      42812895.59       62611211.59       77340051.5
T15      43023317.01       62755879.47       77358132.12
T16      43573596.81       63576950.02       78388429.7
T17      44130479.97       64407873.42       79431090.86
T18      44694045.73       65248767.9       80486263.95
T19      45264374.28       66099753.11       81554099.12
T20      45841546.77       66960950.15       82634748.31
T21      46425645.33       67832481.55       83728365.28
;

*existing generation at each time period
Table p_Kzero(i,t) 'existing generation capacities in MW'
                  T1   T2   T3  T4  T5  T6  T7  T8  T9  T10  T11  T12  T13  T14  T15  T16
T17  T18  T19  T20  T21
ExNuc              11419 11419 11419 9879 9879 9879 9363 9363 8050 6686 6170 4487 2792
1911  515  515  515  515  515  515    0
ExGas                4578  4578  4578 4578 2473 2473 2308 2308 2004 1897 1691 1236 1236
1236 1236 1105 1105 1105 1105 1105 1105
ExHydro             6129  6129  6129 6129 6129 6129 6129 6129 6129 6129 6129 6129 6129
6129 6129 6129 6129 6129 6129 6129 6129
ExCoal             6434  6434  6434 6434 4969 3293 3293 3293    0    0    0    0    0    0    0    0
0   0    0    0    0
Nuc                  0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
SCGas                0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
CCGas                0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
Bio                0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
SHydro               0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
MHydro               0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
LHydro               0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
0
;

parameter  r             'interest rate';
```

```
        r = .04;

parameter p_H(s)       'Hours of year for demand block s'
**Assuming hours for each status: peak 4 hr/day, interm 8 hr/day, Base 12 hr/day
         /Peak 1460, Intermediate 2920, Base 4380/;


*old generators are given approximate age values for the sake of division by 0 error
*These values should not matter as the model is not allowed to invest in any of them
parameter age(i)       'Age of generators'
        /ExNuc 30,
        ExCoal 10,
        ExGas 20,
        ExHydro 100,
        Nuc 30,
        SCGas 20,
        CCGas 20,
        Bio 20,
        SHydro 75,
        MHydro 80,
        LHydro 100/;

parameter p_maxcap(i)   'Maximum new capacity of each generation type (MW)'
        /ExNuc inf,
        ExCoal inf,
        ExGas inf,
        ExRnw inf,
        Nuc inf,
        SCGas inf,
        CCGas inf,
        Bio inf,
        SHydro 318,
        MHydro 703,
        LHydro 3591/;

parameter p_VOC(i)      'Variable operating cost of generation type i in year ($/MWh)'
        /ExNuc 1.5,
        ExCoal 0.5,
        ExGas 2.7,
        ExHydro 0.03,
        Nuc 1.5,
        SCGas 3.5,
        CCGas 2.75,
        Bio 4,
        SHydro 1,
        MHydro 1.5,
```

```
LHydro 1.5/;

parameter VOCgrowth(i)   'Annual variable cost growth for each type of generation'
                /ExNuc 0.03,
                ExCoal 0.01,
                ExGas 0.05,
                ExHydro 0.03,
                Nuc .03,
                SCGas .05,
                CCGas .05,
                Bio 0.03,
                SHydro .015,
                MHydro .015,
                LHydro .015/;

parameter p_VC(i,t)       'Present worth of variable cost per unit of capacity for each generator
type i in each time period in $/MWh';
                p_VC(i,t) = p_VOC(i)*((1+VOCgrowth(i))** (ord(t)-1))/((1+r)**ord(t));


parameter fuel(i)        'fuel cost for each generator in $/ MWh'
                /ExNuc 6,
                ExCoal 27,
                ExGas 56,
                ExHydro 0,
                Nuc 6,
                SCGas 56,
                CCGas 56,
                Bio 23,
                SHydro 0,
                MHydro 0,
                LHydro 0/;

parameter fuelgrowthn(i) growth rate for fuel for each new generator
               /ExNuc 0.02,
                ExCoal 0.01,
                ExGas 0.05,
                ExHydro 0,
                Nuc 0.02,
                SCGas 0.05,
                CCGas 0.03,
                Bio 0.03,
                SHydro 0,
                MHydro 0,
                LHydro 0/;
```

```
parameter  p_FC(i,t)     'Variable fuel cost of generation type i in year ($/MWh)';
                 p_FC(i,t)= fuel(i)*(1+fuelgrowthn(i))/((1+r)**ord(t));

parameter  p_C(i,t)      'Total amount of variable cost (FC AND VC) for each generator type i
in each time period in $/MWh';
                 p_C(i,t) = p_VC(i,t) + p_FC(i,t);

*cost of constructing old generators is assigned a high value to deter investment in them
parameter  buildcost(i)  'Construction cost of building a new generator type i in $/KW'
                 /ExNuc 50000,
                 ExCoal 50000,
                 ExGas 50000,
                 ExHydro 50000,
                 Nuc 2970,
                 SCGas 665,
                 CCGas 1174,
                 Bio 2096,
                 SHydro 3700,
                 MHydro 2750,
                 LHydro 2000/;

parameter  p_Inv(i,t)    'Investment amount in new capacity type i in year t ($/MW)';
                 p_Inv(i,t)= buildcost(i)*1000*((22-ord(t)+1)/age(i))/((1+r)**(ord(t)));

parameter  p_up(i)       'maximum ramp up rate (fraction per minute)'
                 /ExNuc 0.0020,
                 ExCoal 0.0093,
                 ExGas 0.0105,
                 ExHydro 0.012,
                 Nuc 0.0020,
                 SCGas 0.0119,
                 CCGas 0.0081,
                 Bio 0.014,
                 SHydro 0.012,
                 MHydro 0.0102,
                 LHydro 0.006/;

parameter  p_dn(i)       'maximum ramp down rate (fraction per minute)'
                 /ExNuc -0.0039,
                 ExCoal -0.011,
                 ExGas -0.0127,
                 ExHydro -0.012,
                 Nuc -0.0039,
                 SCGas -0.0123,
                 CCGas -0.0114,
                 Bio -0.0120,
```

```
                    SHydro -0.0131,
                    MHydro -0.0083,
                    LHydro -0.0063/;

Table  p_Rup(t,s)    'maximum rate of change upward of demand in year t, block s (MW/min)'
        Peak         Intermediate    Base
T1*T21    36.4          41.7          42.6
;

Table   p_Rdn(t,s)      'maximum rate of change downward of demand in year t, block s (MW/min)'
        Peak         Intermediate    Base
T1*T21    -47          -42.7         -33.4
;

parameter   p_BP(t)        'maximum wind ramp from base to peak increased in proportion to predicted annual wind output (MW)'
                    /T1       94.00,
                     T2       128.48,
                     T3       209.05,
                     T4       252.02,
                     T5       346.84,
                     T6       415.16,
                     T7       467.72,
                     T8       611.04,
                     T9       991.44,
                     T10      1081.57,
                     T11      1171.70,
                     T12      1171.70,
                     T13      1261.83,
                     T14      1351.96,
                     T15      1532.23,
                     T16      1532.23,
                     T17      1532.23,
                     T18      1532.23,
                     T19      1532.23,
                     T20      1532.23,
                     T21      1532.23/;

parameter  p_BI(t)       'maximum wind ramp from base to intermed increased in proportion to predicted annual wind output (MW)'
                    /T1       85.00,
                     T2       116.18,
                     T3       189.03,
                     T4       227.89,
                     T5       313.63,
```

```
                    T6       375.41,
                    T7       422.93,
                    T8       552.53,
                    T9       896.52,
                    T10      978.02,
                    T11      1059.52,
                    T12      1059.52,
                    T13      1141.02,
                    T14      1222.52,
                    T15      1385.52,
                    T16      1385.52,
                    T17      1385.52,
                    T18      1385.52,
                    T19      1385.52,
                    T20      1385.52,
                    T21      1385.52/;

 parameter  p_IP(t)      'maximum wind ramp from intermed to peak increased in proportion to
predicted annual wind output (MW)'
                   /T1       56.00,
                    T2       76.54,
                    T3       124.54,
                    T4       150.14,
                    T5       206.63,
                    T6       247.33,
                    T7       278.64,
                    T8       364.02,
                    T9       590.65,
                    T10      644.34,
                    T11      698.04,
                    T12      698.04,
                    T13      751.73,
                    T14      805.43,
                    T15      912.82,
                    T16      912.82,
                    T17      912.82,
                    T18      912.82,
                    T19      912.82,
                    T20      912.82,
                    T21      912.82/;

*=================================================================
============================
* 3. Declare variables.

Variables
```

ob_TC 'Objective function total cost of investment and generation';

Positive Variables
v_PO(i,t,s) 'Power output level of type i generation in year t during demand block s (MW)'
v_K(i,t) 'Total capacity of type i during year t (MW)'
v_NK(i,t) 'New added capacity of type i during year t (MW)'
v_BP(i,t) 'Amount produced by each generator i during t to make up from change in wind from base to peak'
v_BI(i,t) 'Amount produced by each generator i during t to make up from change in wind from base to inter'
v_IP(i,t) 'Amount produced by each generator i during t to make up from change in wind from inter to peak'

;

*==
* 4. Specify the equations and declare the model.

Equations
TotalCost 'define objective function'
DemandBalance(t,s) 'Demand forecast must equal amount of power generated'
CapacityConst(i,t,s) 'You cannot produce more power than you have capacity for'
CurrentCapacity(i,t) 'Capacity available equal to previous capacity depreciated plus new capacity invested'
MaxPotentialCap(i) 'Physical and other limitation on how much of each capacity can be built'
MaxRateOfChangeUp(t,s) 'ramp up rate of generation cannot exceed maximum allowed rate of change upward'
MaxRateOfChangeDn(t,s) 'ramp down rate of generation cannot exceed maximum allowed rate of change downward'
HourRampLimitUpBP(i,t) 'restricting generators from ramping up from base to peak by more than what the time allows'
HourRampLimitUpBI(i,t) 'restricting generators from ramping up from base to intermediate by more than what the time allows'
HourRampLimitUpIP(i,t) 'restricting generators from ramping up from intermediate to peak by more than what the time allows'
HourRampLimitDnPI(i,t) 'restricting generators from ramping down from peak to intermediate by more than what the time allows'
HourRampLimitDnPB(i,t) 'restricting generators from ramping down from peak to base by more than what the time allows'
HourRampLimitDnIB(i,t) 'restricting generators from ramping down from intermediate to base by more than what the time allows'
TotalWindChangeBP(t) 'ensuring the generators make up a predetermined drop in wind from base to peak'

```
TotalWindChangeBI(t)       'ensuring the generators make up a predetermined drop in wind from base to intermediate'
TotalWindChangeIP(t)       'ensuring the generators make up a predetermined drop in wind from intermediate to peak'

;


TotalCost..               ob_TC =e= sum(i, sum(t, sum(s, p_C(i,t)*p_H(s)*v_PO(i,t,s) ) ) )
                          + sum(i, sum(t, p_Inv(i,t)*v_NK(i,t) ) ) ;

DemandBalance(t,s)..       sum(i, v_PO(i,t,s)*p_H(s) ) - p_D(t,s) =e= 0  ;

CapacityConst(i,t,s)..     v_K(i,t) =g= v_PO(i,t,s) + v_BP(i,t) + v_BI(i,t) + v_IP(i,t)  ;

CurrentCapacity(i,t)..     v_K(i,t) =e= p_Kzero(i,t) + sum(tt$((ord(tt)<=ord(t)) AND (ord(tt)>=max(1,(ord(t)-age(i)+1)))), v_NK(i,tt)) ;

MaxPotentialCap(i)..       sum(t, v_NK(i,t)) =l= p_maxcap(i);

MaxRateOfChangeUp(t,s)..   sum(i, p_up(i)*v_K(i,t)) =g= p_Rup(t,s);
MaxRateOfChangeDn(t,s)..   sum(i, p_dn(i)*v_K(i,t)) =l= p_Rdn(t,s);

HourRampLimitUpBP(i,t)..   p_up(i)*60*v_K(i,t)*12 + v_PO(i,t,'base') =g= v_PO(i,t,'peak') + v_BP(i,t) ;
HourRampLimitUpBI(i,t)..   p_up(i)*60*v_K(i,t)*12 + v_PO(i,t,'base') =g= v_PO(i,t,'intermediate') + v_BI(i,t) ;
HourRampLimitUpIP(i,t)..   p_up(i)*60*v_K(i,t)*5 + v_PO(i,t,'intermediate') =g= v_PO(i,t,'peak') + v_IP(i,t) ;
HourRampLimitDnPI(i,t)..   p_dn(i)*60*v_K(i,t)*3 + v_PO(i,t,'peak') =l= v_PO(i,t,'intermediate')  ;
HourRampLimitDnPB(i,t)..   p_dn(i)*60*v_K(i,t)*1 + v_PO(i,t,'peak') =l= v_PO(i,t,'base') ;
HourRampLimitDnIB(i,t)..   p_dn(i)*60*v_K(i,t)*3 + v_PO(i,t,'intermediate') =l= v_PO(i,t,'base') ;

TotalWindChangeBP(t)..     p_BP(t) =e= sum(i, v_BP(i,t));
TotalWindChangeBI(t)..     p_BI(t) =e= sum(i, v_BI(i,t));
TotalWindChangeIP(t)..     p_IP(t) =e= sum(i, v_IP(i,t));

*no new investments can be made in old power plants:
v_NK.fx("ExNuc",t)= 0;
v_NK.fx("ExCoal",t)= 0;
v_NK.fx("ExGas",t)= 0;
v_NK.fx("ExHydro",t)= 0;
```

```
Model GenerationExpansion /all/ ;
Solve GenerationExpansion minimizing ob_TC using lp ;
```